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FORECASTING AIRCRAFT MISHAPS USING MONTHLY MAINTENANCE REPORTS

by

John S. Van Houten

September, 1994

Thesis Advisor: Peter A. W. Lewis

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Naval Aviation aircraft mishaps continue to be of great concern due to the high cost of loss of life and aircraft. The goal of this thesis is to develop a predictive statistical model that accurately forecasts Marine Corps AV-8B Harrier aircraft mishaps based on existing monthly maintenance reports. Monthly maintenance reports provide numerous independent variables based on personnel levels and maintenance hours that could possibly be used to forecast aircraft mishaps. These variables were graphically analyzed to determine any relationships that could be exploited in developing the model. Higher order relationships were investigated by the method of principal components and logistic regression. After a thorough analysis, there appears to be no combination of variables in this particular data that could be used to forecast aircraft mishaps. The overall result of the thesis is that there is no relationship between monthly maintenance reports and aircraft mishaps that can be exploited to develop a predictive statistical model.

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FORECASTING AIRCRAFT MISHAPS USING MONTHLY MAINTENANCE REPORTS

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Submitted in partial fulfillment
of the requirements for the degree of

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from the

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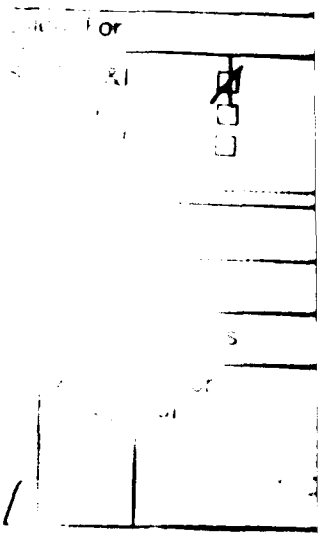
September 1994



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ABSTRACT

Naval Aviation aircraft mishaps continue to be of great concern due to the high cost of loss of life and aircraft. The goal of this thesis is to develop a predictive statistical model that accurately forecasts Marine Corps AV-8B Harrier aircraft mishaps based on existing monthly maintenance reports. Monthly maintenance reports provide numerous independent variables based on personnel levels and maintenance hours that could possibly be used to forecast aircraft mishaps. These variables were graphically analyzed to determine any relationships that could be exploited in developing the model. Higher order relationships were investigated by the method of principal components and logistic regression. After a thorough analysis, there appears to be no combination of variables in this particular data that could be used to forecast aircraft mishaps. The overall result of the thesis is that there is no relationship between monthly maintenance reports and aircraft mishaps that can be exploited to develop a predictive statistical model.

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EXECUTIVE SUMMARY

Aircraft mishaps continue to be a major concern to the Marine Corps due to the high costs associated with the loss of life and aircraft. A predictive statistical model or quantitative formula that identifies, on the basis of prior months maintenance reports, a squadron at risk of having a mishap would greatly enhance the commanding officer's ability to prevent mishaps. This thesis attempts to develop a predictive statistical model which identifies high risks squadrons based on existing monthly maintenance reports. That is, we want to attempt to identify a set of conditions in previous months maintenance records which presage with high probability a mishap in the next month. Every squadron is required to submit monthly maintenance reports that detail the type and amount of maintenance performed on each aircraft in that month and report maintenance personnel levels within the squadron. Many experienced people involved in Naval Aviation believe that they should be able to use these monthly reports to identify a squadron at risk of having a mishap.

The Marine Corps is looking for a predictive statistical model that includes all aircraft types, but because of possible different operating environments and procedures between aircraft types, this thesis focuses on one particular aircraft. If a powerful predictive statistical model is developed for this particular aircraft, then there is hope that the analysis and the statistical model could be expanded to include all aircraft types. The scope of the thesis has been narrowed to developing a predictive statistical model for the Marine Corps AV-8B Harrier aircraft.

The overall goal of the predictive statistical model is to identify high risk squadrons based on existing monthly maintenance and personnel reports, and not to determine the cause of mishaps. The statistical model will not determine if

a squadron is doing the correct amount of maintenance or if the squadron is adequately manned, but rather given the reported numbers, is the squadron at high risk of having a mishap.

The predictive statistical model will be developed by determining in which of the variables, or combination of the variables, there is a significant difference in the previous months maintenance pattern of a mishap and a non-mishap squadron. These variables can then be used with various statistical prediction and classification methods to attempt to forecast high risk squadrons.

A graphical analysis indicated that there were no one or two dimensional relationships that could be used to classify a mishap squadron. And furthermore, the techniques of principal components and logistic regression did not produce any higher order relationships that could be used to classify a mishap squadron.

Based on this particular analyzed data there apparently is no relationship between existing monthly maintenance reports and aircraft mishaps. This may indicate that there is no relationship between the level of maintenance and mishaps, but the results also might indicate that a monthly generated report may not be useful in predicting an aircraft mishap. The fact that the data is reported once a month, at the end of the month, could conceal any useful subtle changes or indications of a high risk squadron that occur during the month.

Two alternative recommendations are evident. The first alternative is to accept that there may be no exploitable relationship between monthly maintenance reports and aircraft mishaps and focus elsewhere to determine a predictive statistical model that forecasts aircraft mishaps. The second alternative recommendation is that further analysis be done, possibly attempting to use daily maintenance reports versus

monthly maintenance reports to determine a predictive statistical model that forecasts aircraft mishaps.

I. INTRODUCTION

A. PROBLEM STATEMENT

Aircraft mishaps continue to be a major concern to the Marine Corps due to the high costs associated with the loss of life and aircraft. A predictive statistical model or quantitative formula that identifies, on the basis of prior months maintenance reports, a squadron at risk of having a mishap would greatly enhance the commanding officer's ability to prevent mishaps. This thesis attempts to develop a predictive statistical model which identifies high risks squadrons based on existing monthly maintenance reports. That is, we want to attempt to identify a set of conditions in previous months maintenance records which presage with high probability a mishap in the next month. Every squadron is required to submit monthly maintenance reports that detail the type and amount of maintenance performed on each aircraft in that month and report maintenance personnel levels within the squadron. Many experienced people involved in Naval Aviation believe that they should be able to use these monthly reports to identify a squadron at risk of having a mishap.

The following is a problem statement from a September 1993 Marine Corps aviation safety standdown:

1. **Topic**: Identify high risk aircraft units.

2. **Discussion**: Commanders must understand and use all available statistical and subjective readiness indicators to evaluate the risk level of their operational aircraft units. Many readiness indicators are available for Commanders to effectively evaluate and strengthen unit readiness, but may not be consistently used. Commander Marine Forces Pacific (MARFORPAC) recommends the Naval Safety Center develop a quantitative formula that assigns risk values to leading indicators which can be used to identify high risk squadrons and forecast and manage risk.

3. **Action**: Safety Division, using the resources available at the Naval Postgraduate School and Naval

> Safety Center, develop a quantitative formula which assigns risk values to squadron aircraft utilization rate, manning rates, mission capable rates, Status of Resources and Training System (SORTS) data, and operations tempo, to identify high risk squadrons. [Ref. 1]

The Marine Corps is looking for a predictive statistical model that includes all aircraft types, but because of possible different operating environments and procedures between aircraft types, this thesis focuses on one particular aircraft. If a powerful predictive statistical model is developed for this particular aircraft, then there is hope that the analysis and the statistical model could be expanded to include all aircraft types. The scope of the thesis has been narrowed to developing a predictive statistical model for the Marine Corps AV-8B Harrier aircraft.

There are obviously thousands of influences on aircraft mishaps but this thesis focuses on just existing monthly maintenance reports. It is conjectured that probably the greatest influence on aircraft mishaps is that of the commanding officer's attitude concerning safety. However this is impossible to quantify and is not included in this study. The operations tempo of a squadron may also greatly influence mishaps but is difficult to quantify, even as a categorical variable, and an acceptable operations tempo variable was not found to include in this thesis. For the preceding reasons, any model developed may not be a powerful model in forecasting mishaps, but could be used as a tool for commanding officers to help identify a squadron at risk of having a mishap.

The overall goal of the predictive statistical model is to identify high risk squadrons based on existing monthly maintenance and personnel reports, and <u>not to</u> determine <u>the cause</u> of mishaps. The statistical model will not determine if a squadron is doing the correct amount of maintenance or if the squadron is adequately manned, but rather given the

reported numbers, is the squadron at high risk of having a mishap.

The predictive statistical model will be developed by first determining in which of the variables, or combinations of the variables, there is a significant difference in the previous months maintenance pattern of a mishap and a non-mishap squadron. These variables can then be used with various statistical prediction and classification methods to attempt to forecast high risk squadrons.

B. HISTORICAL BACKGROUND

A Defense Technology Information Center search did not produce any related references on the topic of predicting aircraft mishaps based on monthly maintenance reports. A report titled "Marine Corps Aviation Mishap Rate Assessment Study" dated February 1992 includes some analysis of a similar problem. [Ref 2.] The study attempted to explain why the Marine Corps 1990 mishap rate was alarmingly high.

One section of the study tested the hypothesis that there exists a high correlation between increases in Direct Maintenance Man Hours per flight hour and the increase in mishap rate for 1990. For the test, data on Not Mission Capable Supply, cannibalization, aircraft utilization, and mishap rates were presented to the Naval Safety Center, Statistics and Mathematics Department for analysis. The study team was not able to demonstrate a correlation between aircraft utilization rates and support resources as independent variables and mishap rate as the dependent variable. The study team concluded:

> It is still intuitively appealing that there is a relationship and experts in the field, the operators and senior officers, firmly believe that the relationship is valid. [Ref. 2]

The study suggested two different alternatives. The first alternative is to conclude that the relationship between utilization resources and mishaps is undefined and perhaps unimportant. The second alternative is to continue research to define the relationship between aircraft utilization, support resources like direct maintenance man hours per flight hour and parts, and the mishap rate.

This thesis approaches the latter alternative. The previous study includes all Marine Corps aircraft combined and focused on the relationship with mishap rate. This thesis is defined more in that it focusses on one particular aircraft and attempts to predict mishaps, rather than mishap rates.

C. TECHNICAL BACKGROUND

The goal of any statistical model developed would be to accurately classify a squadron as a mishap or non-mishap squadron in the next month based on the current month maintenance reports. The monthly maintenance report data consists of numerous maintenance variables that are believed to possibly influence mishaps. Hopefully, a function can be developed which uses these predictor variables to classify a squadron as a mishap squadron. Therefore, a discriminate function is needed that projects some combination of the predictor variables to a decision space that classifies the squadron as a mishap squadron or not. An example is the following linear additive model:

$$D^k \leftarrow f(x) = f(a_1x_1 + a_2x_2 + \ldots + a_n x_n) \qquad (1)$$

where, D^k = decision space (in k-space)

x_i = ith independent predictor variable

a_i = ith coefficient

i = 1,2, . . ., n.

In other words, if given the function $f(x)$ and a new set of predictor variables x, the model would either classify a squadron as an element of the acceptance region of the mishap decision space, D^*, or not. A graphical explanation is shown in Figure 1. The idea is to develop a function that maps the n-space independent predictor variables to an outcome, or decision space, that is partitioned into an accept and reject region so as to determine if a mishap may occur.

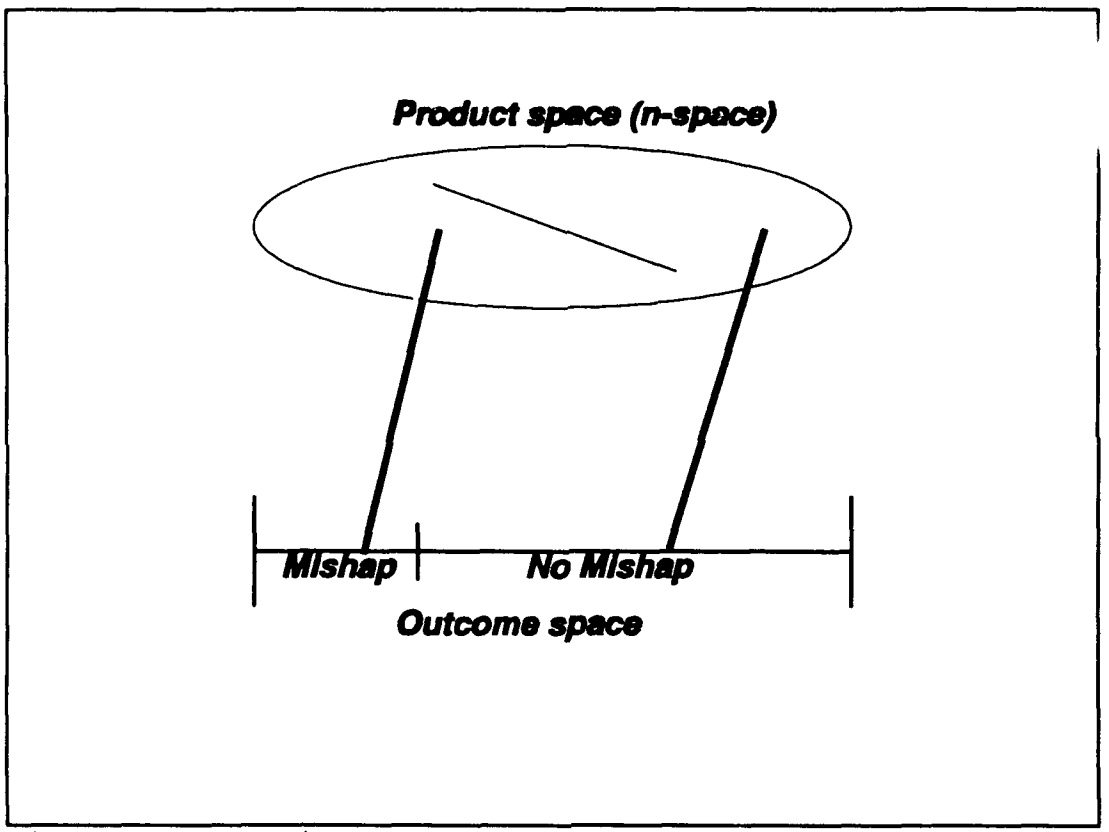

Figure 1. Mapping n-space to the outcome space.

Identifying the function capable of this classification is not the only problem. Any statistical model developed from this function must be accurate in its forecast so that the model will be useful. But the statistical model also needs to minimize the probability of making errors.

The two types of errors that are of concern are type I and type II errors. A type I error is defined as rejecting that the outcome is from the event population, when it actually is from the event population. In this statistical model a type I error is when a squadron is classified as a non-mishap squadron when it is actually a mishap squadron. The probability of a type I error is given by

$$\alpha = Pr(\textit{predict non-mishap} \mid \textit{actually a mishap}). \quad (2)$$

A type II error is defined as accepting that the outcome is from the event population when it actually is not from the event population. In this statistical model a type II error is when a squadron is classified as a mishap squadron when it is actually not a mishap squadron. The probability of a type II error is given by

$$\beta = Pr(\textit{predict mishap} \mid \textit{actually no mishap}). \quad (3)$$

Obviously the type I error is the more serious of the two errors in this statistical model since a mishap occurs that was not predicted. But a high probability of a type II error, although no mishap occurred, can render the model useless. If the probability of a type II error is high, it means that the model is predicting an unacceptable number of squadrons as mishap squadrons when they are non-mishap squadrons.

Any model developed needs to minimize the probabilities of the type I and type II errors as much as possible, while still providing accurate predictions. The two types of errors are interrelated in that if one type of error is minimized it is usually at the expense of the other. Generally, if the probability of a type I error is minimized, while ignoring the probability of a type II error, the probability of making a type I error may be satisfactory but the probability of making a type II error will be unsatisfactorily high. In this statistical model this may result in an acceptable level of

type I errors, failing to predict a mishap when a mishap actually occurs, but an unacceptable level of type II errors, predicting a mishap when a mishap did not occur. Obviously the type I error would be the lowest if all squadrons were predicted as mishap squadrons, because there would be no type I errors. But the type II errors would be maximized, since most of the squadrons would have a false alarm, rendering the model useless.

Dividing the data into mishap and non-mishap observations creates two separate populations with numerous independent predictor variables. Marginal analysis of each of these univariate independent predictor variables from the separate populations can determine if there exists a significant difference between a mishap and non-mishap squadron with respect to that particular variable alone. For example, maybe the classification is a function of just one variable, i.e.

$$D^1 \sim f(x) = f(a_n x_n) . \qquad (4)$$

To determine if there is a significant difference in the distribution of a variable among two populations it is assumed that the two populations have similar distributions with possibly different parameters. To graphically show differences, the density traces of the variables from each population are superimposed on the same density plot. Any significant differences can be determined by comparing the two traces.

For example, this technique could be used if trying to determine significant differences in a predictor variable from separate populations, non event and event observations. Figure 2 shows two superimposed density traces of a variable from two separate populations that show the obvious significant difference of the event observations variable being larger than the non event observation variable. In this

example the plotted variable could possibly be used to classify an observation as an event or non event by setting the rejection region at **w**. Thereby accepting that a new set of values come from the non event population if the outcome is less than **w**. As can be seen in this example, a model using the example variable would be very powerful, with a low probability of both types of error. But if the density traces shift so that they are now overlapping more, then using the same **w** will result in the exact same type I error while the type II error will increase dramatically.

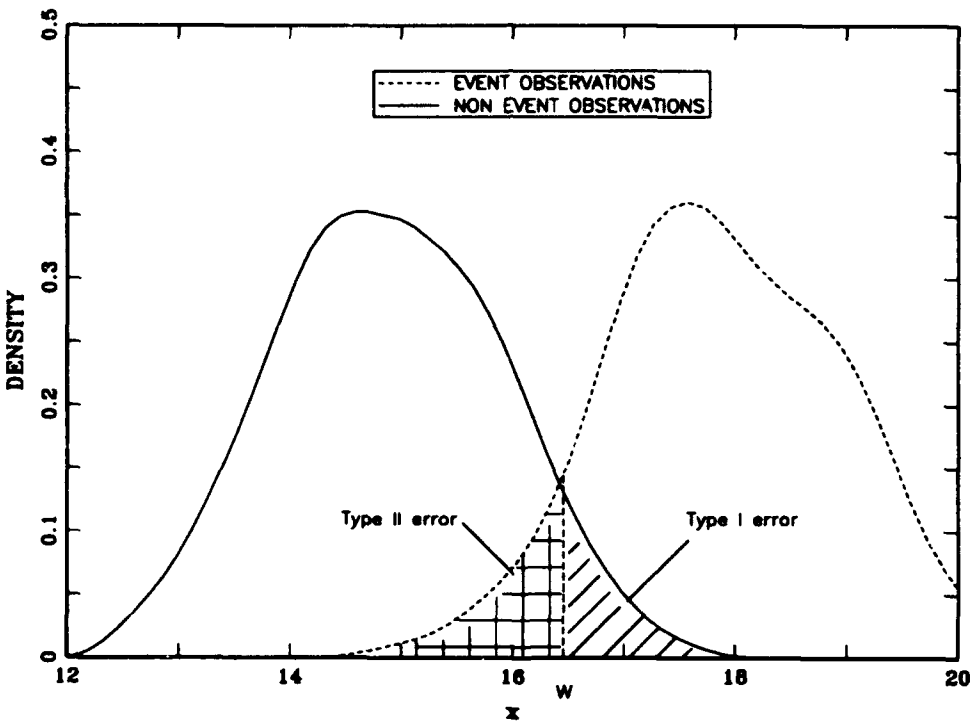

Figure 2. Density trace comparisons of one dimensional data with a significant difference in population density.

On the other hand, Figure 3 shows two superimposed density traces of a variable from two separate populations that show no obvious significant differences between non event and event observations. In this example, there is no way that this variable could be used to classify a squadron as a mishap or non-mishap squadron because there is no rejection region that can be identified that could be used to distinguish between

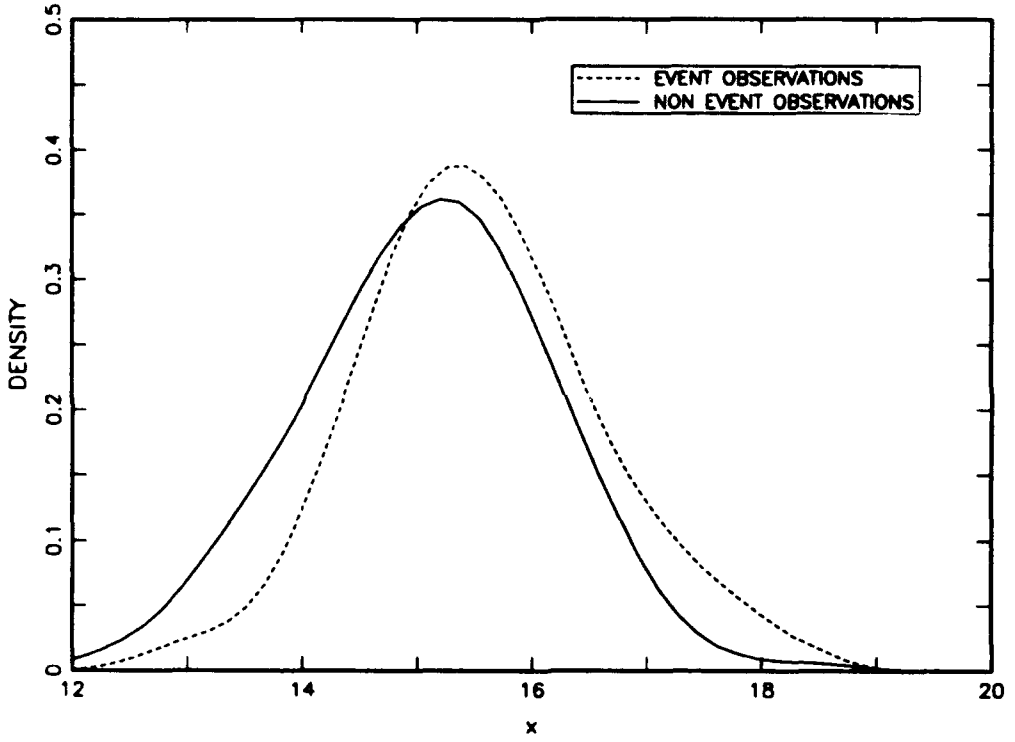

Figure 3. Density trace comparisons of data with no significant difference in population density.

the two populations with a high degree of accuracy.

The above discussion uses just an analysis of the univariate independent predictor variables to attempt to classify an observation as an event or a non event. It is also possible that combinations of independent variables may produce the function that classifies the dependent variable as

in Equation 1. Producing a coded scatter plot of each independent variable versus each other independent variable may produce a clustering of observations that could be used to classify the dependent variable as an event observation. A coded scatter plot provides a three dimensional display by having the two independent predictor variables plotted against each other and having separate symbols showing event and non event observations. This provides an easy way to determine if any observations are clustering, i.e., if most of the event observations are grouped together it shows that the combination of variables may produce a model that can classify the observation as an event or non event.

Figure 4 shows an example of two independent variables, x and y, that are being used to attempt to discriminate between two populations on the basis of x and y. A plot of x and y with the two separate populations coded could show any clustering of the dependent variable. As can be seen in Figure 4, there is no rejection region that can be used to separate the two populations and classify an event or non event with a high degree of accuracy.

Figure 5 shows that when the observations are from the event population all of the observations are in a tight and separated cluster. This shows the possibility of using x and y to classify an observation as an event or non event. As can be seen in Figure 5, by setting the rejection region at the indicated line, the event and non event observations can be accurately classified. For example, the indicated rejection line in Figure 5 is a function of x and y that maps to a point in a two-space decision space

$$D^2 \leftarrow f(x,y) = f(a_x x + a_y y) \qquad (5)$$

where, a_x and a_y are the coefficients of x and y.

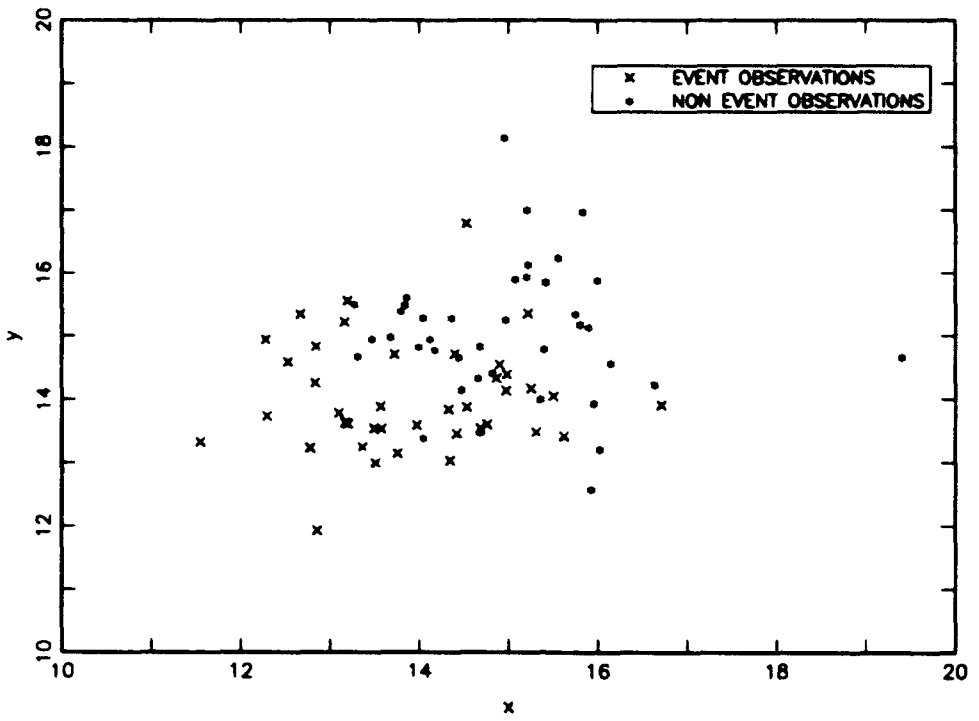

Figure 4. Coded scatter plots showing no breakout or clustering of event observations.

So, given any x and y, the function will map the observation onto the decision space and if the point lies below the acceptance region dividing line then that observation is classified as an event. Whereas, if the point lies above the acceptance region dividing line then that observation is classified as a non event.

Obviously, higher order combinations of the function can provide the predictive statistical model. Instead of graphical analysis, the higher order functions are investigated by multivariate techniques such as discriminate analysis, logistic regression, and cluster analysis.

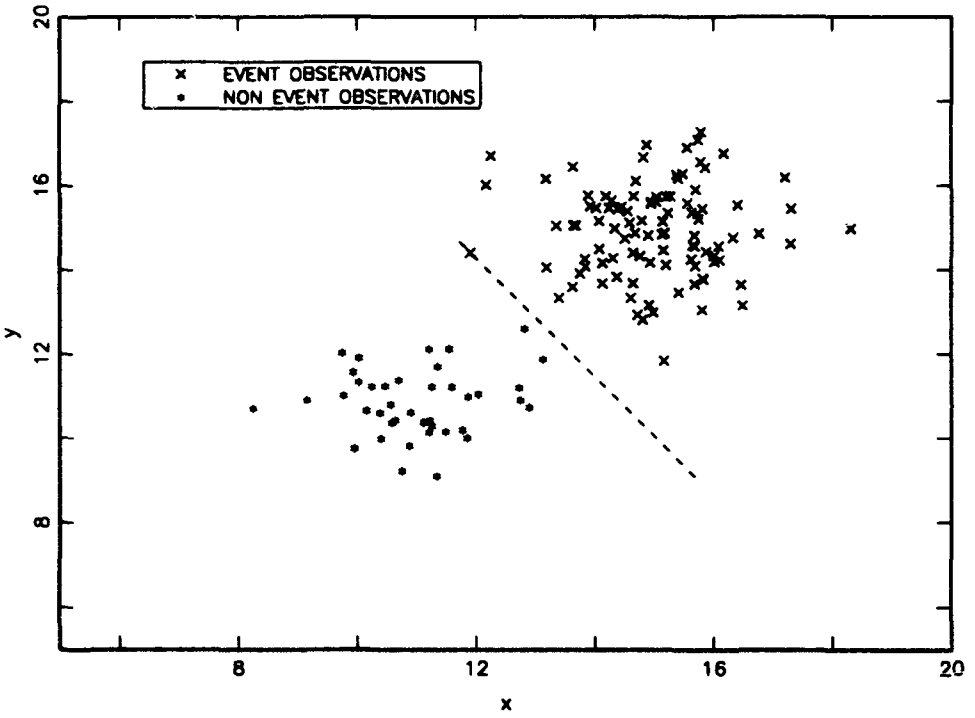

Figure 5. Coded scatter plot showing a significant breakout or clustering of event observations.

II. DATA OVERVIEW

A. DATA DESCRIPTION

1. Mishap Data

The aircraft mishap data was provided by Headquarters Marine Corps Aviation Safety Division and includes data on nine AV-8B Harrier squadrons over the time period of January 1990 to November 1993. The data consisted of the date, severity, squadron, and brief description of all Flight Mishaps involving Harriers in this period. A naval aircraft Flight Mishap is defined as an unplanned event directly involving naval aircraft which there was $10,000 or greater aircraft damage, or loss of aircraft, and intent for flight existed at the time of the mishap. Table I shows the definitions of the mishap severity classes based on personal injury and property damage. Any occurrence in which total cost of property damage is less than $10,000 and there are no defined injuries, is not considered a reportable naval aircraft mishap.

The description of the mishap is an excerpt from the Mishap Investigation Report that provides a short narration of the causal factors of the mishap. The causal factors can be divided into three basic categories. The first is mishaps caused by human factors, i.e., human error by the aircrew, supervisory personnel, maintenance personnel, or facilities. The second factor is a material failure, i.e., a component fails causing the mishap. And the last is mishaps caused by an aircraft hitting a bird.

All three severity classes of mishaps (A, B, and C) were combined to form a dependent variable that indicates if a squadron had a mishap in a month or did not have a mishap in that month. All casual factors were combined except for the birdstrike mishaps. Since there is no credible way to predict

Mishap Severity	Description
Class A	A mishap in which the total cost of property damage is $ 1,000,000 or greater; or a naval aircraft is destroyed or missing; or any fatality or permanent total disability occurs with direct involvement of naval aircraft.
Class B	A mishap in which the total cost of property damage is $ 200,000 or more, but less than $ 1,000,000; or a permanent partial disability, or hospitalization of five or more personnel.
Class C	A mishap in which the total coat of property damage is $ 10,000 or more, but less than $ 200,000; or injury results in one or more lost workdays.

Table I. Classifications of Naval Aircraft Mishaps. From Ref [3].

birdstrike mishaps, they were not considered a mishap month in the analysis. All of the remaining mishaps observations were included in belief that the mishap observations and independent predictor variables could be used to develop a statistical model that can discriminate a mishap and non-mishap squadron based on monthly maintenance reports. In three separate cases a squadron that had two mishaps in the same month was included as a single observation of a mishap month.

2. Maintenance Data

The maintenance data was provided by the Naval Safety Center through the Naval Aviation Logistic Data Analysis system. This data consisted of the Equipment Condition Analysis report and the maintenance man hours per flight hour for the nine squadrons. The Equipment Condition Analysis

report data consisted of the reported Aviation Maintenance and Material Management (3M) system data for each squadron in each month. The amount of maintenance hours is divided into separate categories based on the information on the Maintenance Action Form. The Maintenance Action Form is the paperwork that describes particular maintenance to be done and assigns the maintenance to the appropriate work center [Ref. 4]. Included in this data for each squadron is:

1. Date by month from January 1990 to November 1993.

2. Average number reporting inventory: average number of aircraft assigned in each month.

3. Flight hours: total flight hours in each month.

4. Number sorties: total number of flights in each month.

5. Number landings: total number of landings in each month.

6. Hours Equipment in Service: total number of hours that the aircraft were available for use in each month.

7. Hours Not Mission Capable Maintenance-Scheduled: total number of hours that aircraft were not capable of performing any of their missions due to scheduled maintenance requirements in each month. Scheduled maintenance is the periodic prescribed inspection/ servicing of equipment, done on a calendar or hours of operation basis. An aircraft is considered Not Mission Capable Maintenance-Scheduled only if panels and equipment removed to conduct area inspections cannot be replaced within two hours.

8. Hours Not Mission Capable Maintenance-Unscheduled: total number of hours that aircraft were not capable of performing any of their missions due to unscheduled maintenance requirements in each month. All not mission capable maintenance hours that are not Not Mission Capable Maintenance-Scheduled are classified as Not Mission Capable Maintenance-Unscheduled. Unscheduled maintenance is performed when corrective maintenance is required.

9. Hours Not Mission Capable Supply: total number of hours that aircraft were not capable of performing any of their missions because maintenance required to clear the discrepancy cannot continue due a supply shortage.

10. Hours Partially Mission Capable Maintenance-Unscheduled: total number of hours that the aircraft were capable of performing at least one, but not all of their missions due to unscheduled maintenance requirements in each month.

11. Hours Full Mission Capable Maintenance-Unscheduled: total number of hours that aircraft were capable of performing all of their missions but are not at optimum performance due to unscheduled maintenance requirements in each month.

12. Maintenance Man Hour per Flight Hour: average number of hours of maintenance done per flight hour in each month. Derived by dividing total maintenance hours by total hours flown.

The maintenance data was reduced somewhat. The number of landings was obviously highly correlated with the number of sorties, therefore the number of landings was omitted since the number of sorties provides essentially the same information. The hours Equipment in Service was perfectly correlated with the average number of aircraft assigned since the total hours equipment in service is the average number of aircraft multiplied by the total number of hours in the month. Therefore the hours equipment in service was not included in the analysis. If a squadron had numerous missing data in a particular month that month was deleted from the data. And, if the amount of flight hours in a month was less than 100, then that month was deleted since that month was obviously not a normal operating month and may skew any results of the analysis.

3. Personnel Data

The personnel data was provided by Headquarters Marine Corps and consisted of the number of each maintenance related

Military Occupational Specialty in each squadron in each month. Eight squadrons were included in this data. The data provided was the number of each specialty, and was not compared with the squadron Table of Organization to determine if a squadron was manned at a level consistent with the Table of Organization. The data consisted of quarterly data from January 1990 to December 1992 and monthly data from February 1993 to November 1993. The month of January 1993 was missing from the data. The following is the brief description of the provided Military Occupational Specialties:

1. Aircraft Mechanic: responsible for engine repair, daily inspection, and launching and recovering aircraft.

2. Aircraft Maintenance Chief: senior enlisted person in maintenance department. Usually only a couple in entire squadron, one as maintenance chief, responsible for overseeing the department, and one as a the maintenance control chief, responsible for assigning maintenance on a particular aircraft to the responsible work center.

3. Aircraft Maintenance Administrative Clerk and Aircraft Maintenance Data Analysis Technician: responsible for tracking maintenance and preparing required reports.

4. Aircraft Maintenance Hydraulics and Pneumatics Mechanic: responsible for maintenance of the hydraulic systems and aircraft body maintenance.

5. Flight Equipment Marine: responsible for maintenance of aircrew personal flight equipment.

6. Aircraft Maintenance Ground Support Equipment Mechanic: responsible for maintenance on ground support equipment used in the maintenance of the aircraft.

7. Aircraft Safety Equipment Mechanic: responsible for maintenance of ejection seats and environmental systems.

8. Aircraft Communications/Navigation System Technician: responsible for maintenance of communications/navigation and related systems.

9. Aircraft Electrical System Technician: responsible for maintenance of electrical systems.

10. Avionics Maintenance Chief: senior enlisted in avionics division.

11. Aircraft Ordnance Technician: responsible for ordnance delivery systems and loading of ordnance.

12. Aviation Ordnance Chief: senior enlisted in ordnance division.

All twelve specialties were included in the analysis, although it is doubtful that some of them would effect aircraft mishaps. The aircraft maintenance chief, avionics chief, and ordnance chief specialties probably will not be significantly different between mishap and non-mishap squadrons since all squadrons have just one or two of these specialties and are almost always manned. The data analysis section, the flight equipment section, ground support section, and safety equipment section, probably will not be significantly different between mishap and non-mishap squadrons since maintenance performed by these sections is highly specialized and is rarely, if ever, considered a causal factor in an aircraft mishap.

B. DATA REDUCTION

1. One Month Lag

All of the above data are contained in reports that are generated at the end of the month being reported upon. Hence this data is not useful in trying to predict a mishap in that month since the month is already past. Also, a squadron that has a mishap will sometimes drastically change their operating procedures, obviously effecting the maintenance reports for that month. For the preceding reasons the squadron reported maintenance figures for each month were used as independent variables to attempt to predict a mishap squadron in the next

month. Basically creating maintenance variables with a one month lag as predicting variables for a mishap in the month.

2. Final Data

The original data set contained approximately 432 observations (nine squadrons x 48 months of data) that had 54 mishap observations and 378 non-mishap observations. Each observation consisted of a month with a binary dependent variable indicating if a mishap occurred or not, and 23 possible independent predictor variables. After the above reductions in the data, the final data set used in the analysis contained 368 observations that had 44 mishap observations and 324 non-mishap observations. Each observation includes the binary dependent variable and 21 possible independent predictor variables.

3. Model Formulation

The final data set and model of the problem can be considered similar to Anderson's Iris Data made famous by Fisher [Ref. 5]. In that data set there were measurements from three varieties of flowers and the problem was to develop a model and a procedure that would classify a particular flower, as one of the three varieties. The data set consisted of a set of four measurements on each of 150 flowers; the sample contained 50 flowers of each variety of flower. So this data may be regarded as 150 four-dimensional observations in four-dimensional space. The goal of a model is to develop a function that maps the observations from four dimensional space to some outcome space that will enable the classification of the flower in a particular category. In this example, by plotting petal length versus petal width, and coding each observation, an obvious clustering of type of flowers is shown that can be used to classify each flower.

The final mishap data set is somewhat similar to the above example, but obviously more complex. The final data set was a set of 21 measurements on each of 368 separate monthly observations. The 21 measurements include all of the personnel and maintenance figures discussed previously, for that particular month. The sample contained 324 non-mishap monthly observations and 44 mishap monthly observations. The data can then be regarded as 368 twenty-one dimensional observations in twenty-one dimensional space.

III. DATA ANALYSIS

A. APPROACH TO ANALYSIS

The approach to analysis was to first perform a one-dimensional graphical marginal analysis of each independent predictor variable. A density trace from each population, mishap and non-mishap, for each independent predictor variable was superimposed upon each other to determine any significant differences in the two populations. As discussed earlier, if any of the independent predictor variables indicate a significant difference between the mishap and non-mishap population, that variable or variables, could be used to discriminate an observation as a mishap or non-mishap squadron.

Following the one-dimensional analysis a two-dimensional graphical analysis of the independent predictor variables will be performed to determine any pair of predictor variables that can be used to classify a squadron as a mishap or non-mishap squadron. All pairs of the possible independent predictor variables will be plotted in coded scatter plots to determine which pairs of variables could possibly be used to classify a squadron as a mishap squadron. If any of the coded scatter plots show a clustering of mishap or non-mishap observations, then these pairs of independent variables could possibly be used to discriminate between mishap or a non-mishap squadron.

Following the one and two-dimensional graphical analysis the independent predictor variables will be analyzed in higher dimensions with the multivariate techniques of principal components and logistic regression to attempt develop the predictive statistical model. These techniques will discover any higher order relationship that may be used to classify a squadron as a mishap or non-mishap squadron.

All graphical output was produced using IBM's *A Graphical Statistical System (AGSS)* [Ref. 6] on a 486DX-50 personal computer.

B. PERSONNEL DATA ANALYSIS

The twelve military occupational specialties considered were plotted on density trace plots to determine if there was a first order significant difference in the distributions of the military occupational specialties between a mishap squadron and a non-mishap squadron manning level. All of the plots reveal that there is no discernable area (marginal) effect between a mishap squadron and a non-mishap squadron. All of the density traces of the personnel data are reproduced in Appendix A. A representative plot of the Aircraft Mechanic specialty is shown in Figure 6. As can be seen, there is not a significant difference in the density plots of aircraft mechanics assigned to mishap and non-mishap squadrons.

The manning level results are undoubtedly highly influenced by the fact that most of the personnel data was reported as quarterly figures. Since the same number of personnel was reported for each month of that quarter, the changes between mishap and non-mishap squadrons in each month was not distinguishable.

It bears repeating that the personnel data was compared by the total number of individuals in each specialty. This number was not compared to the Table of Organization since the goal of the thesis was to distinguish between a mishap and non-mishap, and not to determine if a squadron was manned at Table of Organization level. This analysis also had no way of analyzing the experience level of the individuals assigned to different squadrons. It was assumed that the experience level would be similar among squadrons, which may or may not be true. And obviously, the experience level among the

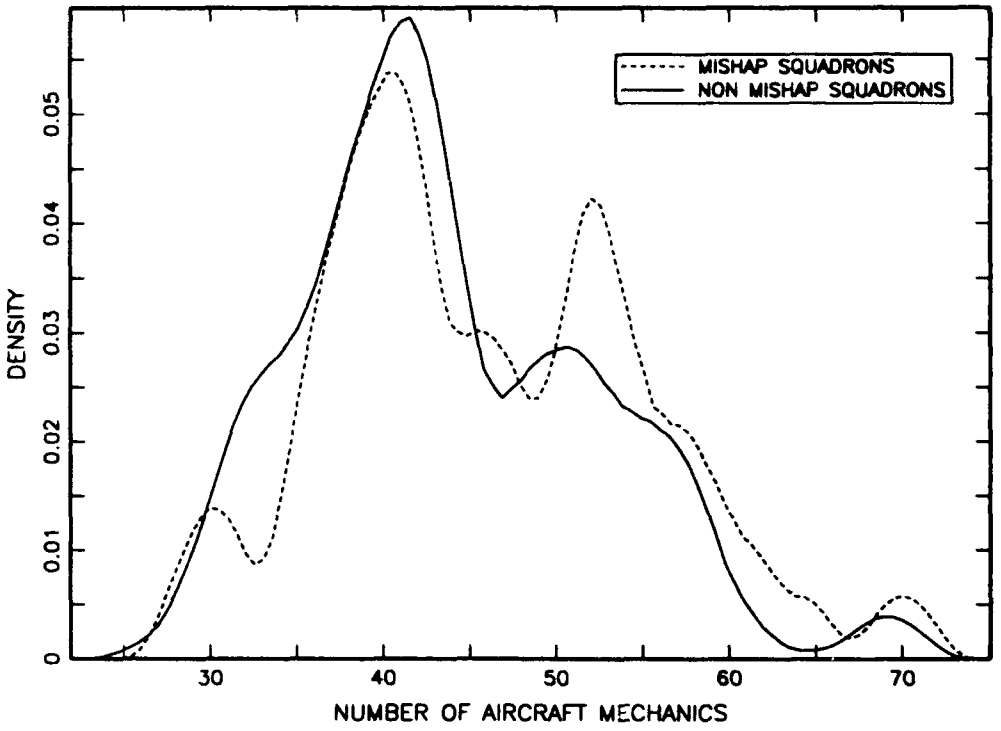

Figure 6. Density traces of Aircraft Mechanics assigned to each squadron.

maintainers could influence the chances of the squadron having a mishap.

Based on the above one-dimensional analysis, the personnel data was not considered significant and therefore was not included in any further analysis.

C. MAINTENANCE DATA ANALYSIS

The marginal analysis of the ten possible maintenance predictor variables was done by plotting density traces of each variable to determine if there was a first order significant difference in the distributions of the variable between a mishap squadron and a non-mishap squadron. All of the density trace plots of the maintenance independent

predictor variables are reproduced in Appendix B. None of the plots revealed any discernable area (marginal) effect in one dimension between a mishap and non-mishap squadron. A representative plot of Maintenance Man Hours per Flight Hour is shown in Figure 7. The figure clearly shows that there is not a significant difference between the maintenance man hours per flight hour per month in the mishap squadron population and non-mishap squadron population. The majority of observations fall between 10 and 25 maintenance man hours per flight hour with no way of separating the mishap from the non-mishap observations.

The one-dimensional analysis of all maintenance independent predictor variables did not produce any

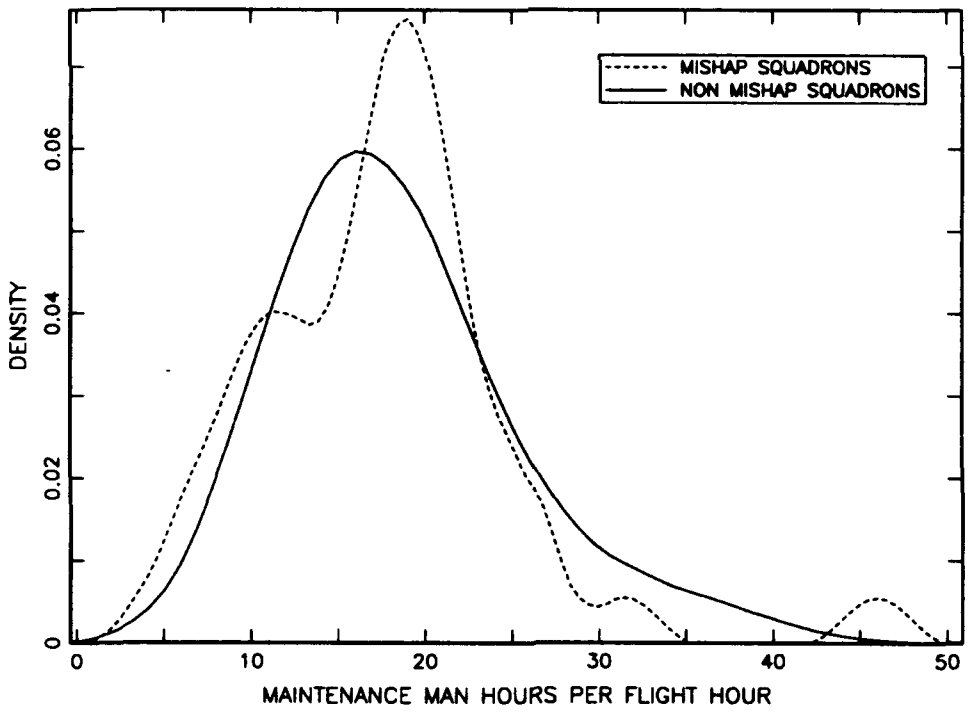

Figure 7. Density trace of Maintenance Man Hours per Flight Hour.

significant differences that could be used to classify a squadron as a mishap or non-mishap squadron, so all of the independent maintenance predictor variables were retained and an analysis of a two-dimensional relationship was performed.

To determine any two-dimensional relationship, all possible pairs of the ten independent maintenance predictor variables were plotted in coded scatter plots. A coded scatter plot is a technique in which each independent variable can be plotted against all other independent variables to determine any second order interaction of variables that could be used in classifying a squadron as a mishap or non-mishap squadron. A coded scatter plot will show the relationship between the two predictor variables, as well as any possible relationship to predict a mishap, i.e., separate clustering of observations that can discern between mishap and non-mishap squadrons. The coded scatter plots showed no discernable area of effect that could be used in discriminating between a mishap and non-mishap squadron. A representative plot is shown in Figure 8 with all the possible pairs of plots reproduced in Appendix C. The coded scatter plots show mishap and non-mishap months as well as identifying the training squadron versus the regular squadrons. The training squadron is shown separately to determine if the training environment is possibly significant in determining mishaps.

In Figure 8 the total Flight Hours of a squadron are plotted against the Maintenance Man Hours per Flight Hour. It is obvious that the training squadron produces more flight hours each month and has a slightly higher maintenance man hours per flight hour. But there are no discernable area of effect exclusive to a mishap or non-mishap squadron. Ideally all the mishap observations would be clustered together, separated from a cluster of all the non-mishap observations.

From the above two-dimensional analysis several transformations of the original independent variables were

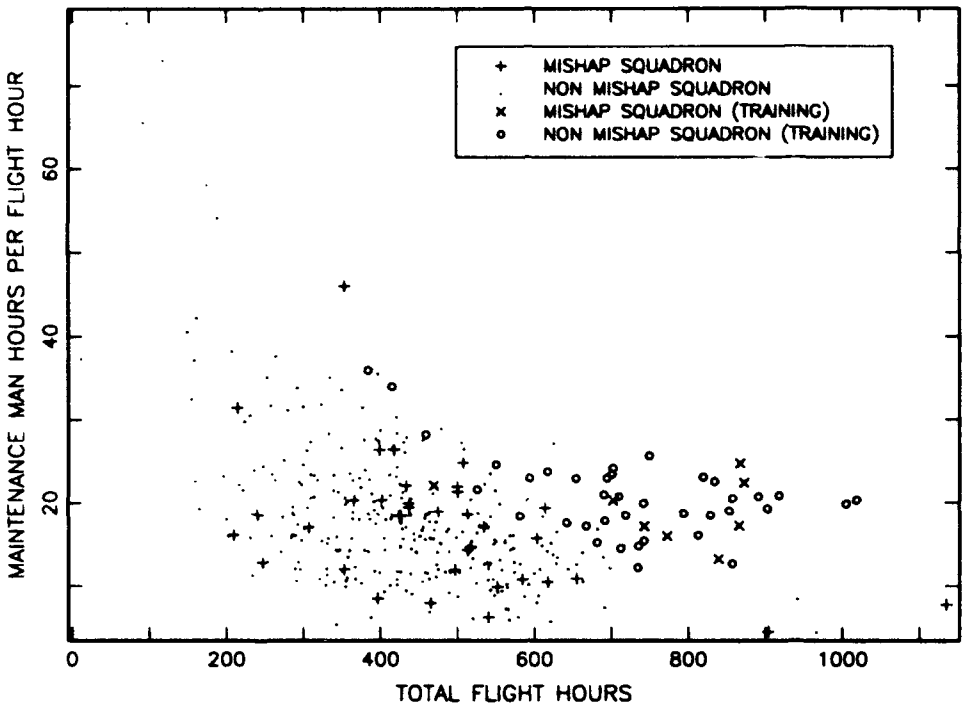

Figure 8. Coded scatter plot of Maintenance Man Hours per Flight Hour versus Total Flight Hours.

suggested. As could be expected, the total number of flight hours and total number of sorties a squadron flies in a particular month are highly correlated, hence are providing the same information. Therefore number of sorties was dropped because the total flight hours provides essentially the same information as total number of sorties.

Since the training squadron is always assigned more aircraft and the other squadrons total assigned aircraft can vary significantly, the total flight hours may be skewed somewhat. Therefore the total flight hours flown in each month were divided by the total aircraft assigned that month, to form a new univariate independent predictor variable of average flight hours per aircraft assigned in each month. This new independent predictor variable is basically an

indicator of the utilization rate of the aircraft in a squadron.

Many of the different maintenance predictor variables were spread over a wide range because of a few unusually high or low reported maintenance months. These months could not be considered outliers, so all maintenance predictor variables were transformed by taking the logarithm of the variable, providing a more presentable plot, without changing any of the existing relationships.

As before, a one-dimensional marginal analysis was performed on the transformed independent predictor variables. A representative density trace of Flight Hours per Aircraft is shown in Figure 9, with the remaining density traces of the transformed independent predictor variables reproduced in Appendix D. The plot clearly shows, as well as all other plots, that there is no discernable area of effect between flight hours per aircraft in the mishap squadron population and non-mishap squadron population.

A two-dimensional analysis was then performed on the transformed predictor variables using coded scatter plots to determine any significant pairs of predictor variables. The eight transformed independent maintenance predictor variables were plotted in a coded scatter plot so that each independent variable could be plotted against all other independent variables to determine any pair of variables that could be used in classifying a squadron as a mishap or non-mishap squadron. The plot showed no discernable area of effect that could be used in discriminating between a mishap and non-mishap squadron. A representative coded scatter plot of the logarithm of Maintenance Man Hours per Flight Hour versus Flight Hours per Aircraft is shown in Figure 10, with the remaining coded scatter plots of the transformed independent predictor variables reproduced in Appendix E. The plot shows mishap and non-mishap months as well as identifying the

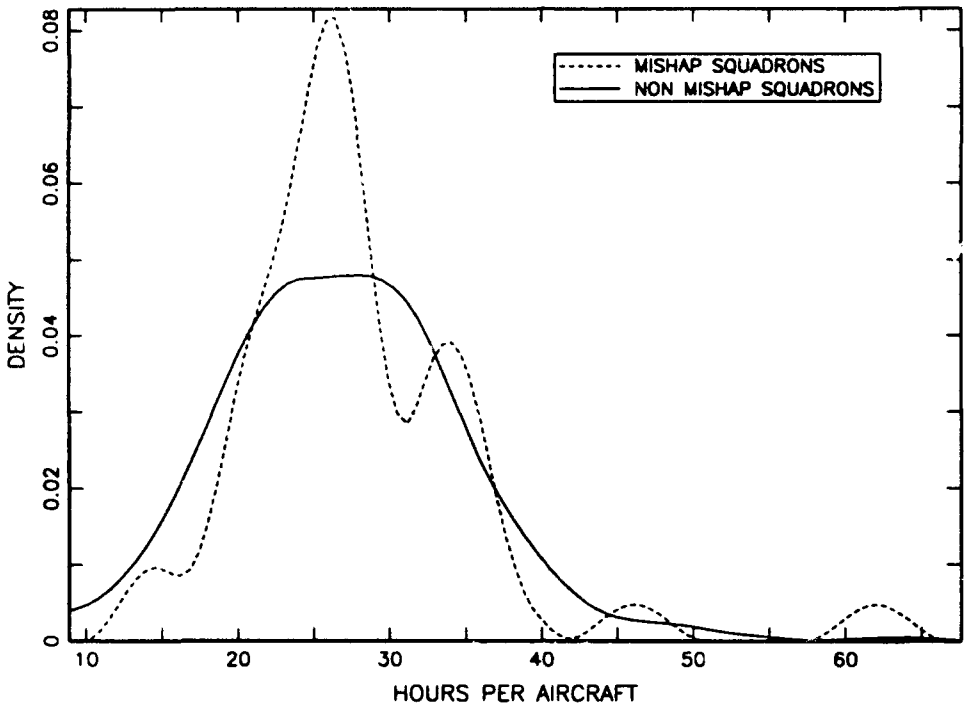

Figure 9. Density trace of Flight Hours per Aircraft.

training squadron versus the regular squadrons. The training squadron is shown separately to determine if the training environment is significant in determining mishaps. Included in each of these plots is a locally weighted regression scatter plot smoothing (LOWESS) function to help indicate any relationship of the two independent variables. [Ref. 7] Except for a few extreme months, the utilization rate and log of Maintenance Man hours per Flight Hour of all the observations, both mishap and non-mishap, are tightly clustered in one group. But there is no discernable clustering of the mishap observations separated from the non-mishap observations. It is somewhat interesting to note that as utilization rate goes up the Maintenance Man hours per Flight Hour decrease, probably due to the fact that the

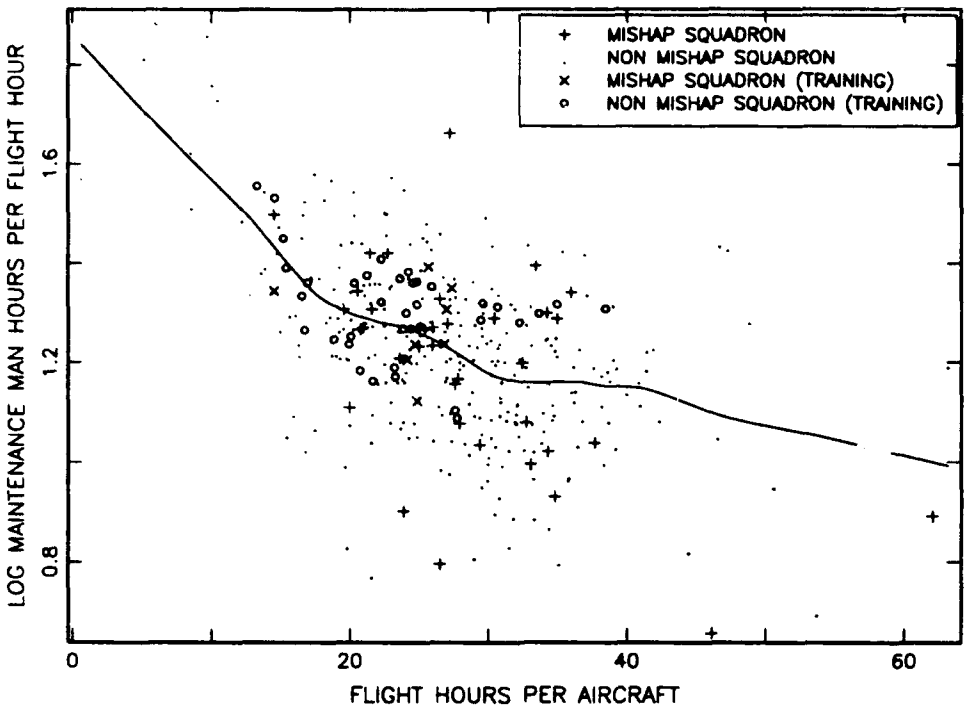

Figure 10. Coded scatter plot of the logarithm of Maintenance Man Hours per Flight Hour versus Hours per Aircraft.

aircraft are up and flying more and not breaking or possibly less time to perform maintenance.

Based on the above one and two dimensional analysis of the original and transformed predictor variables, there does not appear to be any discernable relationships that could be used in classifying a squadron at risk of having a mishap based upon the existing monthly maintenance reports. Since none of the independent variables were determined to be significant in the above graphical analysis, all of the transformed independent maintenance variables were retained as possible predictor variables for an analysis of higher order interactions.

IV. FURTHER ANALYSIS

A. PRINCIPAL COMPONENTS

Since the initial graphical analysis did not reveal any discernable first or second order discriminate function, the method of principal components was used to determine if any linear combination of variables exists that could be used to classify a high risk squadron. The principal component are the independent linear combinations of the existing variables that maximize the variances.

The principal components method in effect rotates the coordinate axes of the data to a new coordinate system that has inherent statistical properties. This is a way of reducing the number of variables to be considered by discarding linear combinations which have small variances and study only those with large variances. The idea is to focus on the largest variances between the variables to help discriminate between mishap and non-mishap squadrons. [Ref. 8]

The data was divided into two separate data sets, a matrix **M**, containing all the maintenance independent predictor variables from the mishap observations and a matrix **N**, containing all the maintenance independent predictor variables from the non-mishaps observations. The non-mishap observations were used as the baseline since the objective of the thesis was to discriminate between mishap and non-mishap observations. The principal components method was applied to the data of non-mishap observations to produce a matrix of principal component coefficients, **P**. The transpose of this matrix was then multiplied by both matrices **M** and **N**, therefore producing matrices whose elements are the baseline component values of the mishap and non-mishap data, $\mathbf{P}^t\mathbf{M} = \mathbf{M}'$ and $\mathbf{P}^t\mathbf{N} = \mathbf{N}'$. The values of the original variables are projected onto the baseline principal axes. To see if these component values are useful for classifying squadrons as mishap and non-mishap

squadrons, the distributions of the first principal component values are compared for significant differences. To compare the principal components, the first principal components of each of the component value matrices was standardized using the mean and standard deviation of the non-mishap observations

$$u'_{i1} = \frac{(n'_{i1} - n'')}{s_{n'}}$$
$$v'_{i1} = \frac{(m'_{i1} - n'')}{s_{n'}} \qquad (6)$$

where,

u'_{i1} is the standardized first principal component of the non-mishap predictor variables.

v'_{i1} is the standardized first principal component of the mishap predictor variables.

n'' and $s_{n'}$ are the average and standard deviation of the first principal component of the non-mishap predictor variables.

n'_{i1} and m'_{i1} are the individual entries in the first column of the two principal component matrices.

These standardized first principal components are then superimposed on a density trace plot. Any significant difference in the two densities of the plot would indicate a transformation of axes that could be exploited to classify the observations as mishap or non-mishap.

Figure 11 shows the resulting standardized first principal component plot of the transformed independent predictor variables. Although there is some difference shown, there is no discernable difference that could be used to discriminate a mishap and non-mishap squadron. Therefore the method of principal components indicates that there may not exist a linear additive model of the independent predictor variables that could be used to classify a mishap or non-mishap squadron.

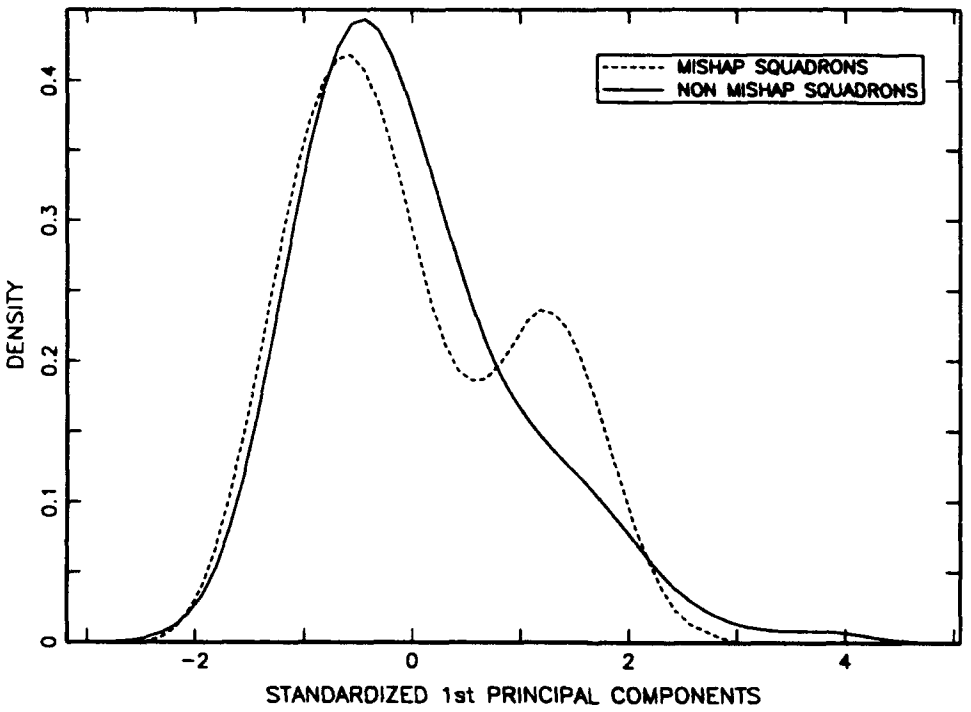

Figure 11. Density trace of standardized 1st principal components of the transformed data.

B. LOGISTIC REGRESSION

To continue to develop a predictive statistical model the method of logistic regression was pursued. Logistic regression uses a linear logistic transformation function that calculates the logarithm of the odds of an event occurring, or the ratio of the probability of success to the probability of failure. That is, the likelihood that an event will occur given a particular set of predictor variables. The logit model takes on the form [Ref. 9]

$$P_i = \frac{1}{1 + e^{-(\alpha + \beta X_i)}}$$

or

$$\log\left[\frac{P_i}{(1 - P_i)}\right] = \alpha + \beta X_i \qquad (7)$$

where P_i = *probability of an event occuring*
X_i = *attributes of an event*
β = *coefficients vector*
α = *scalar.*

Although the individual probability of an event occurring, P_i, are not known, the information for each observation is whether an event occurred or did not occur. The measured dependent variable is $Y_i = 1$, if an event occurred, and $Y_i = 0$, if no event occurred. This dependent variable is used with a maximum likelihood estimation for the logit model to estimate α and β for the model. [Ref. 10] Results from the predictive statistical model provide an estimated forecast of the probability of an event observation occurring based upon a particular set of attributes. Using a selected critical probability, any set of attributes can be classified as an event or non event observation based upon the log odds calculated by the predictive model. The critical probability should be selected so that type I errors are minimized while maintaining an accurate predictive model.

A logistic regression of the aircraft mishap data was performed in attempt to produce a predictive statistical model to forecast aircraft mishaps. Figure 12 shows the superimposed plot of the log odds of the mishap and non-mishap

observations. In this plot the forecasted log odds is the odds of each observation being classified as a non-mishap observation. For example, given a set of predictor variables from a particular squadron, the plot shows the log odds of that squadron being classified as a non-mishap squadron. As can be seen, the log odds of classifying the observations as a non-mishap squadron fall between 0.73 and 0.99, for both mishap and non-mishap observations. This indicates that the predictive model has a high probability of classifying every observation as a non-mishap. There is no critical probability that would partition the decision space that will result in an acceptable predictive statistical model while minimizing errors.

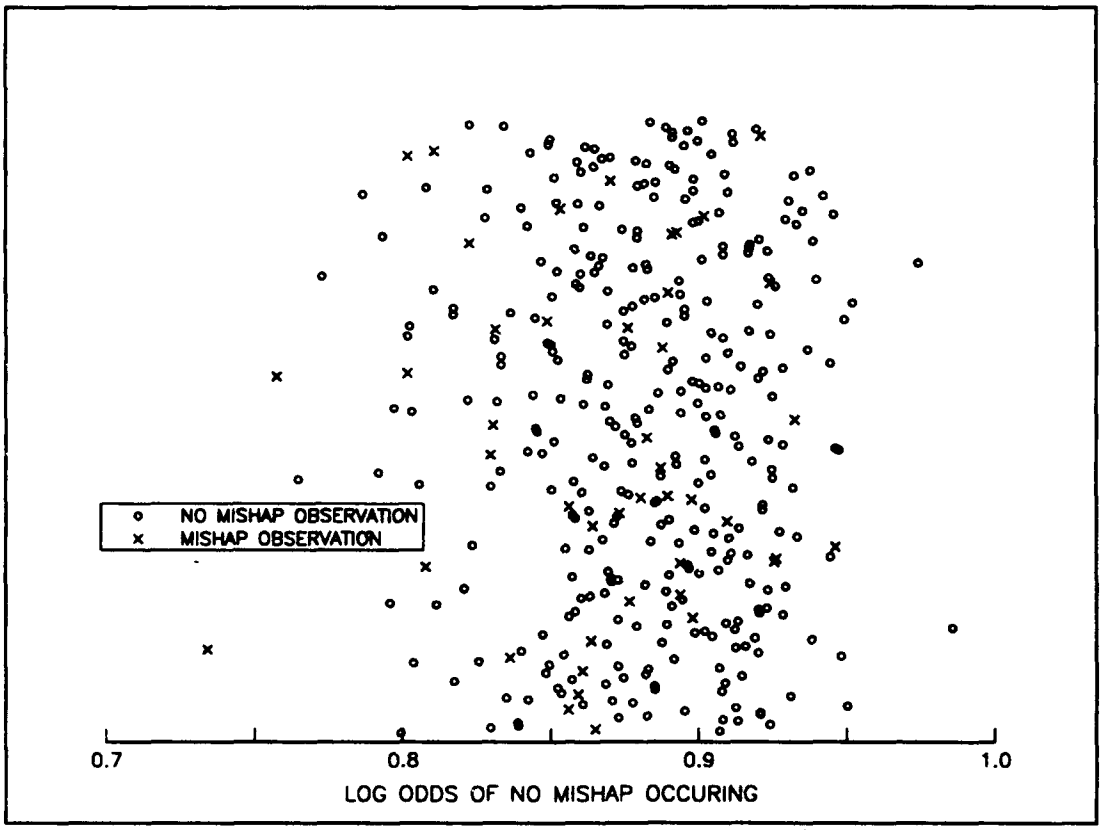

Figure 12. Plot of the log odds of non-mishap and mishap observations produced by logistic regression.

This predictive statistical model is obviously not useful since to forecast a high percentage of mishaps, almost all of

the squadrons would have to be told that they are at a high risk of having a mishap. Obviously, if all the squadrons are told that they are at risk, then the predictive statistical model will soon be disregarded.

C. DATA MANIPULATION

Since all of the preceding detailed analysis failed to provide an acceptable predictive statistical model to forecast mishaps, an attempt to define a model was made by using different subsets of the original data. As stated in the data chapter, all mishaps were included in the original analysis, except for birdstrike mishaps.

Since all the variables were maintenance related, the first transformation eliminated all pilot error mishap observations, so that only mishaps that involved material failure or maintenance personnel error were analyzed. All other observations were considered as non-mishap observations.

The second transformation took the above transformation and further eliminated all Class B and Class C mishap observations. This transformation resulted in a data set of maintenance related Class A mishaps. All other observations were considered as non-mishap observations.

Neither of the above transformations lead to any difference in the outcome of the analysis.

V. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

A. SUMMARY

This thesis has examined the relationship between existing monthly maintenance reports and aircraft mishaps. The reported monthly maintenance and personnel variables were analyzed to determine if any combination of the variables could be used to describe a predictive statistical model that can classify a squadron as a mishap or non-mishap squadron in the upcoming month.

Based upon a graphical analysis there were no obvious one or two dimensional relationships that could be used to classify a mishap squadron. The further techniques of principal components and logistic regression did not produce any higher order relationships that could be used to classify a mishap squadron.

B. CONCLUSIONS

Based on this particular analyzed data there apparently is no relationship between existing monthly maintenance reports and aircraft mishaps. This result might indicate that with this particular data there is no existing relationship, or it might indicate that a monthly generated report may not be helpful in predicting an aircraft mishap. The fact that the data is reported at the end of the month could possible conceal any subtle useful changes or indications that could be exploited to forecast aircraft mishaps.

C. RECOMMENDATIONS

This thesis indicates that there is no relationship between existing monthly maintenance reports and aircraft mishaps that could be used in developing a predictive

statistical model to classify a squadron as a mishap or non-mishap squadron.

Two alternative recommendations are evident. The first alternative is to accept that there may be no exploitable relationship between monthly maintenance reports and aircraft mishaps and focus elsewhere to determine a predictive statistical model that forecasts aircraft mishaps. The second alternative recommendation is that further analysis be done, possibly attempting to use daily maintenance reports versus monthly maintenance reports, to describe a predictive statistical model that forecasts aircraft mishaps.

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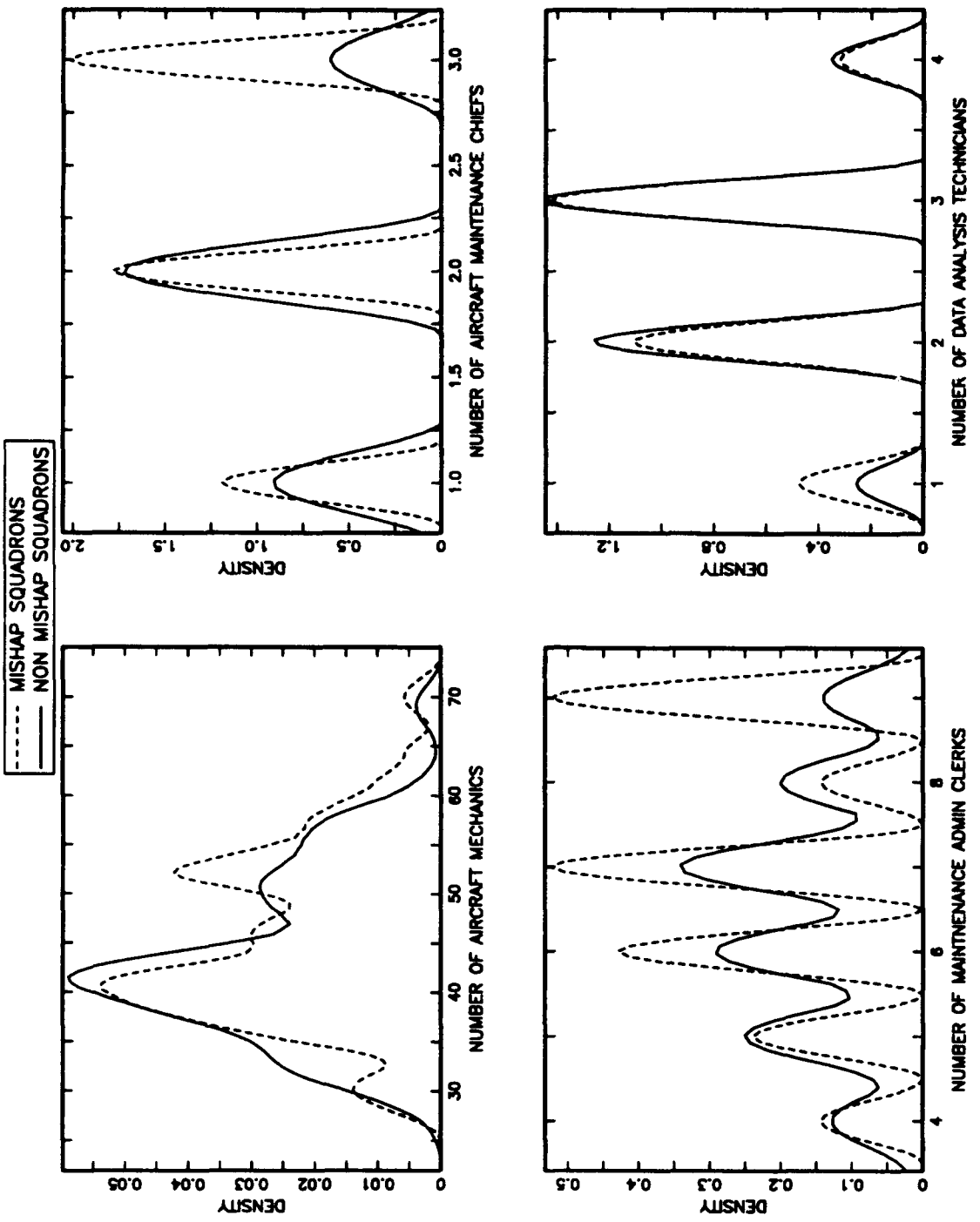
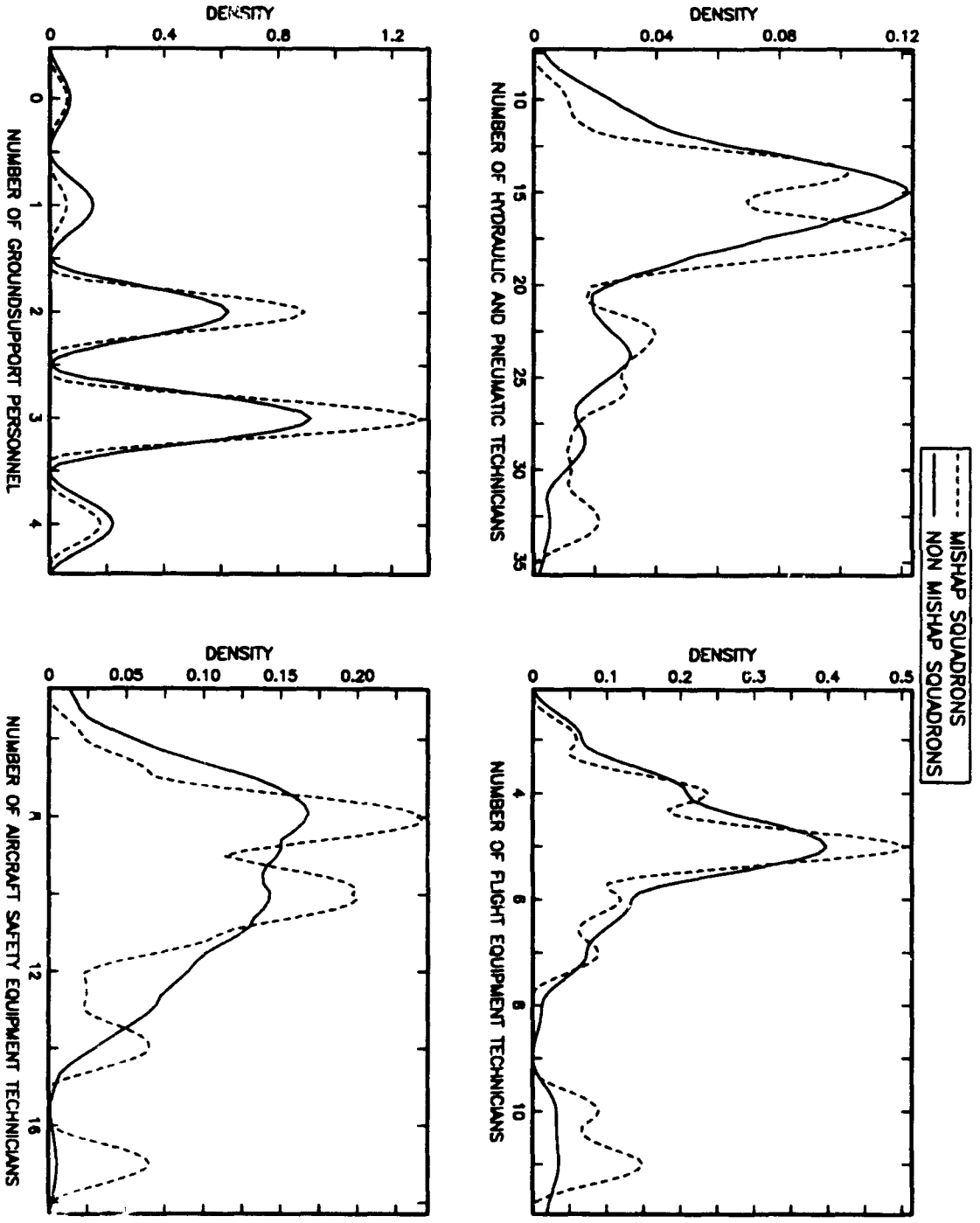
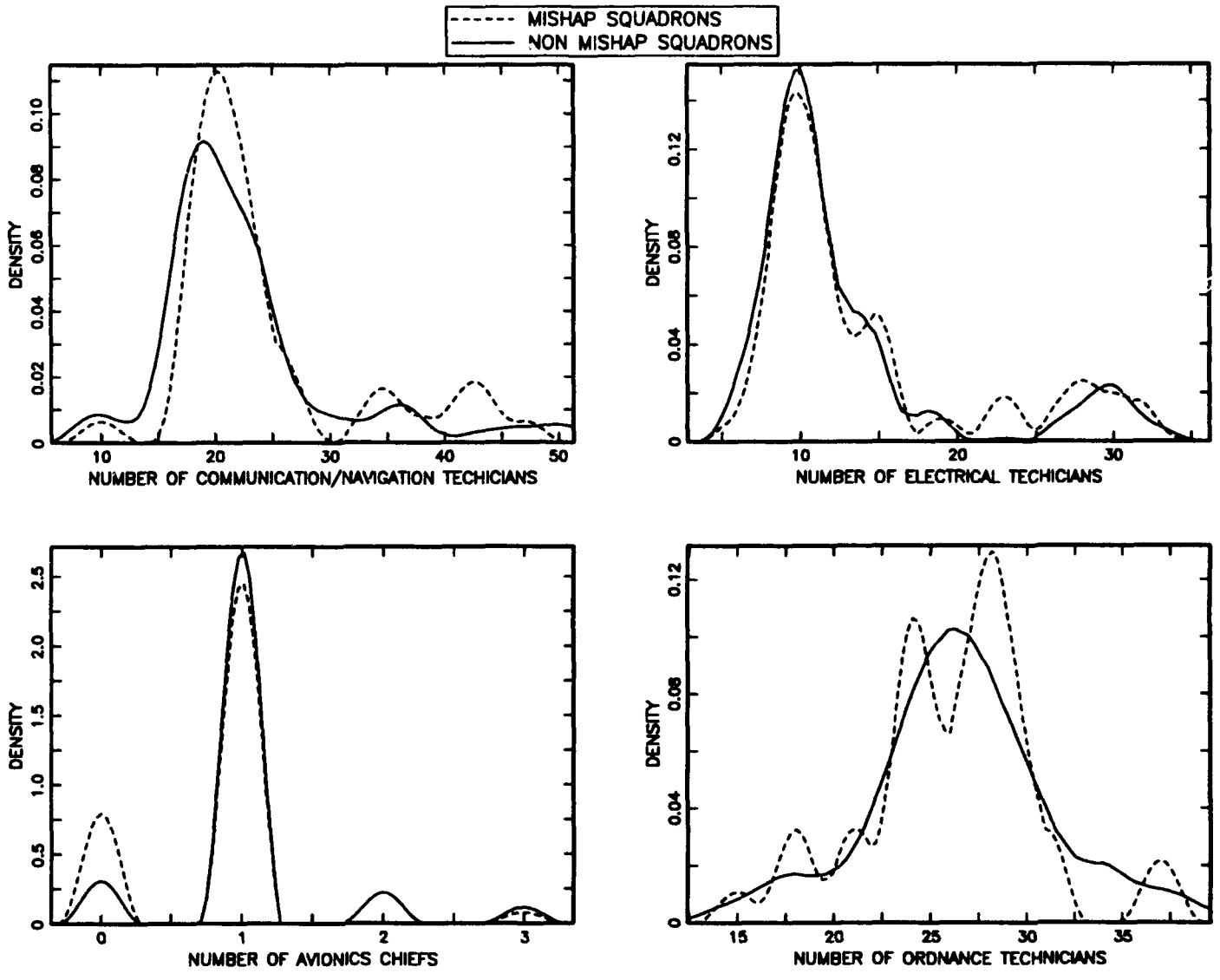
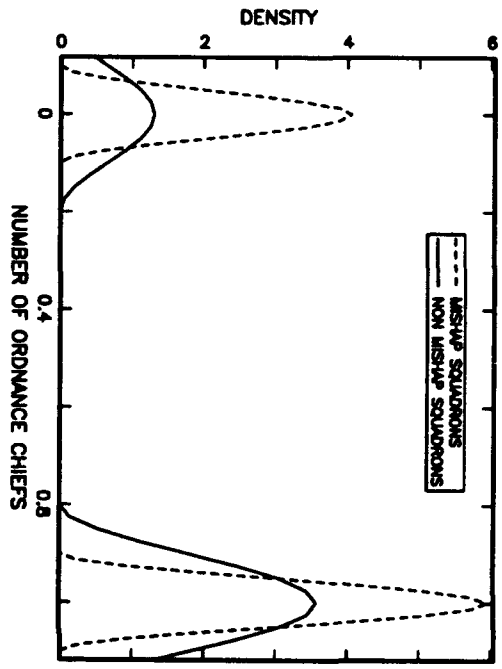
APPENDIX A. MILITARY OCCUPATIONAL SPECIALTY DENSITY TRACES

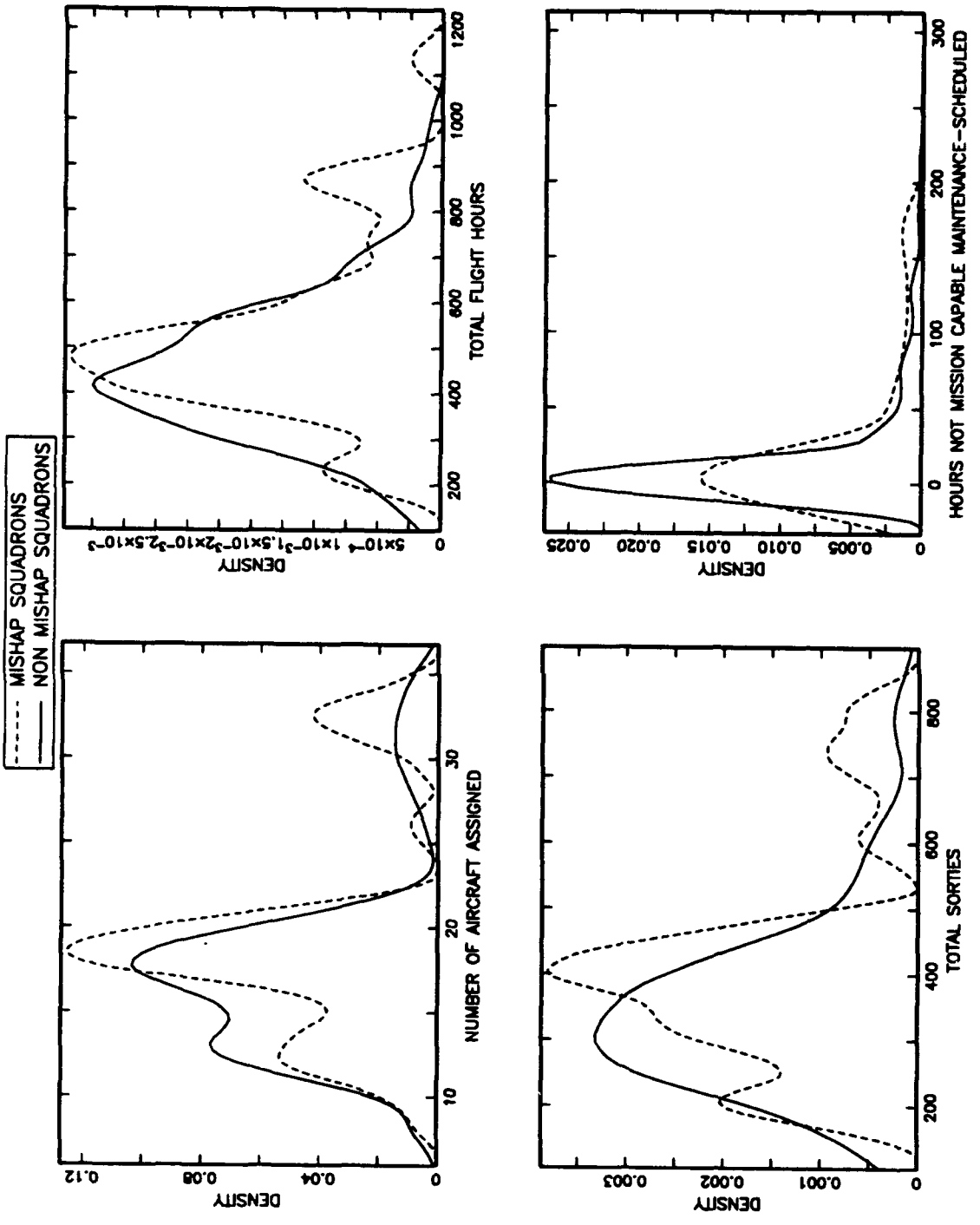


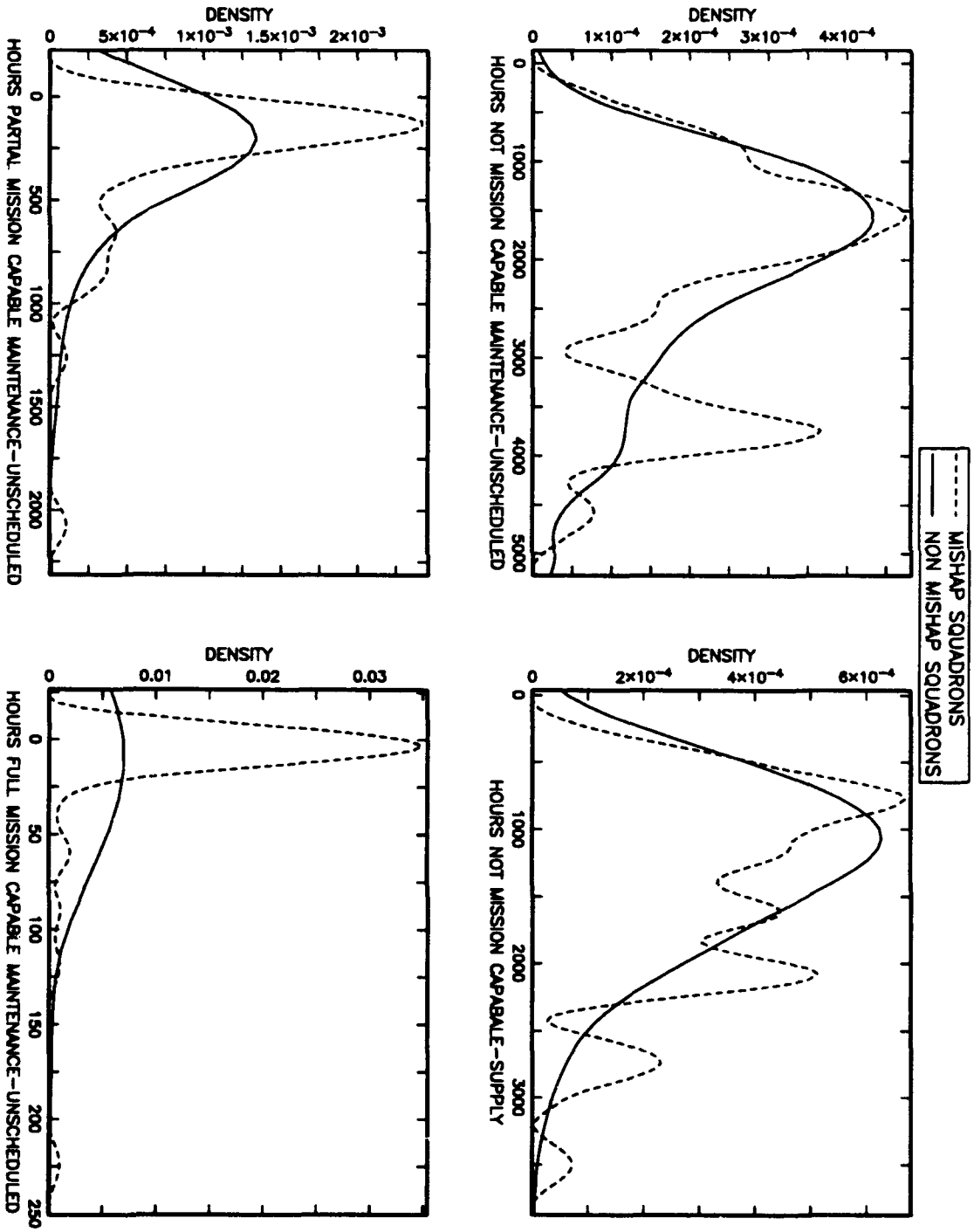

MISHAP SQUADRONS
NON MISHAP SQUADRONS
DENSITY
NUMBER OF HYDRAULIC AND PNEUMATIC TECHNICIANS
NUMBER OF GROUNDSUPPORT PERSONNEL
NUMBER OF FLIGHT EQUIPMENT TECHNICIANS
NUMBER OF AIRCRAFT SAFETY EQUIPMENT TECHNICIANS

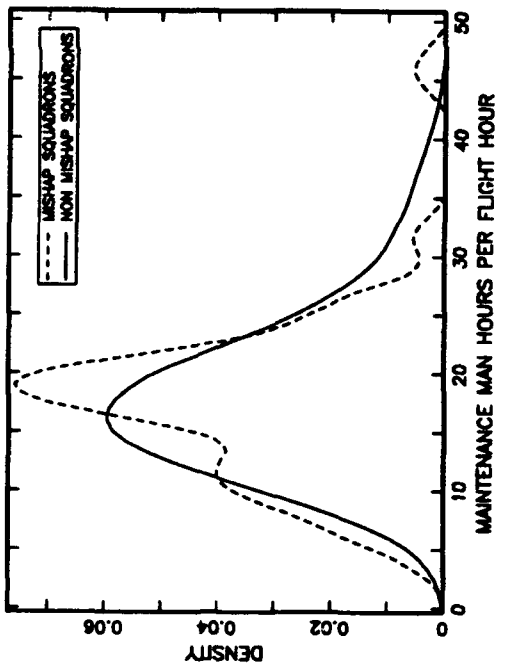

MISHAP SQUADRONS
NON MISHAP SQUADRONS
DENSITY
0
0.02
0.04
0.06
0.08
0.10
10
20
30
40
50
NUMBER OF COMMUNICATION/NAVIGATION TECHICIANS
DENSITY
0
0.04
0.08
0.12
10
20
30
NUMBER OF ELECTRICAL TECHICIANS
DENSITY
0
0.5
1.0
1.5
2.0
2.5
0
1
2
3
NUMBER OF AVIONICS CHIEFS
DENSITY
0
0.04
0.08
0.12
15
20
25
30
35
NUMBER OF ORDNANCE TECHNICIANS


DENSITY
0
2
4
6
0
0.4
0.8
NUMBER OF ORDNANCE CHIEFS
MISHAP SQUADRONS
NON MISHAP SQUADRONS

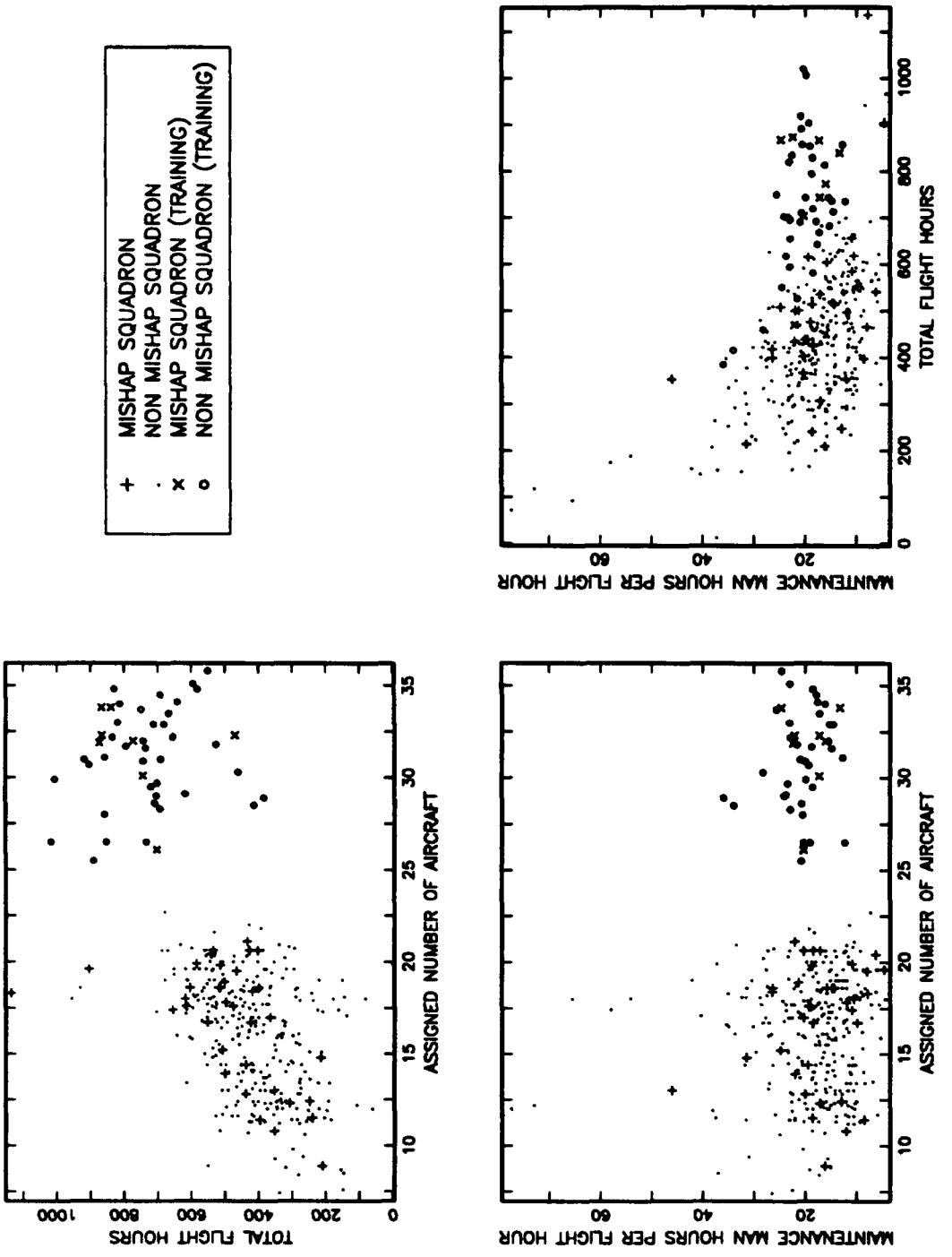
APPENDIX B. MAINTENANCE DATA DENSITY TRACES

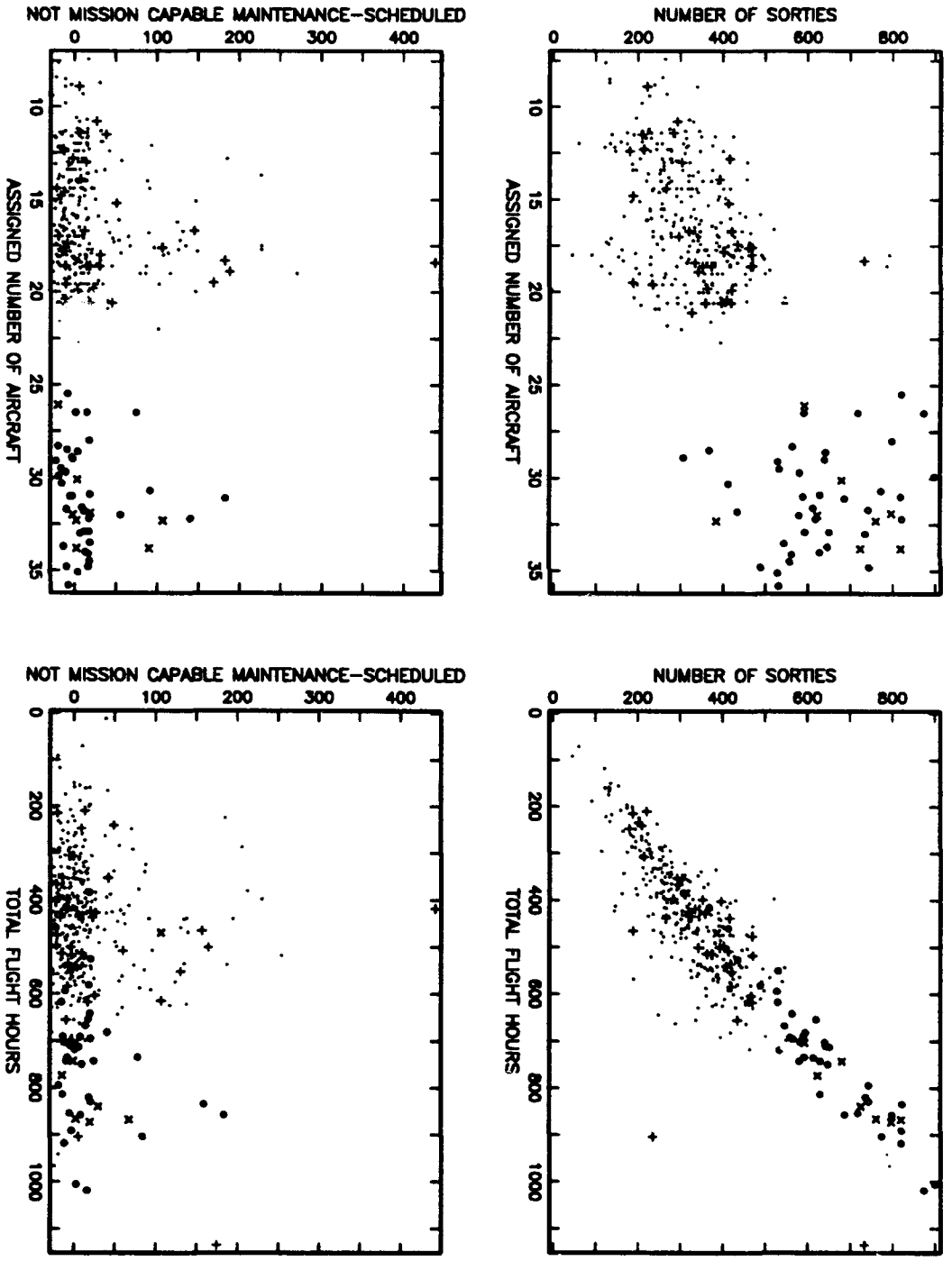


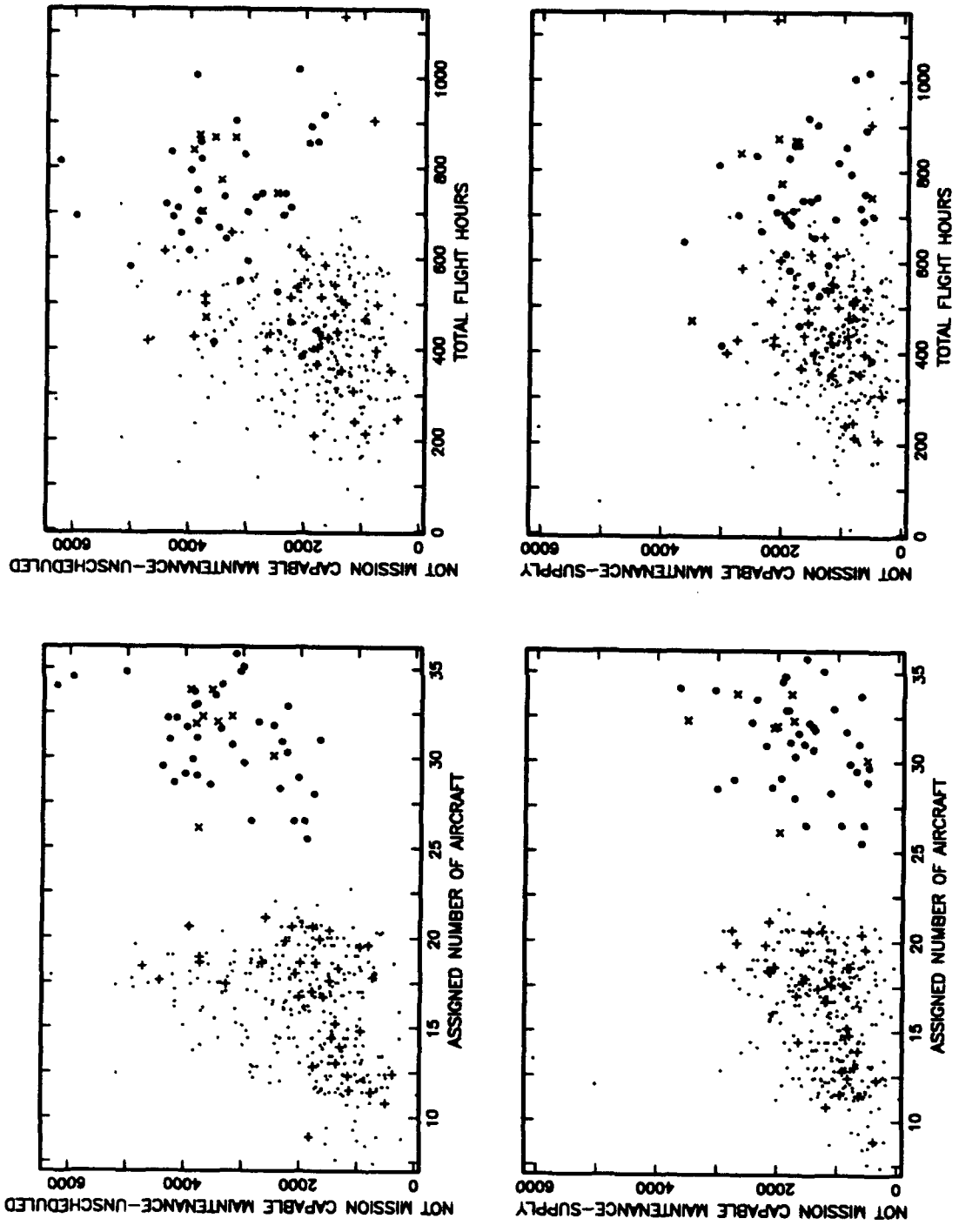

DENSITY
0
5×10⁻⁴
1×10⁻³
1.5×10⁻³
2×10⁻³
HOURS PARTIAL MISSION CAPABLE MAINTENANCE-UNSCHEDULED
0
500
1000
1500
2000
DENSITY
0
1×10⁻⁴
2×10⁻⁴
3×10⁻⁴
4×10⁻⁴
HOURS NOT MISSION CAPABLE MAINTENANCE-UNSCHEDULED
0
1000
2000
3000
4000
5000
MISHAP SQUADRONS
NON MISHAP SQUADRONS
DENSITY
0
0.01
0.02
0.03
HOURS FULL MISSION CAPABLE MAINTENANCE-UNSCHEDULED
0
50
100
150
200
250
DENSITY
0
2×10⁻⁴
4×10⁻⁴
6×10⁻⁴
HOURS NOT MISSION CAPABLE-SUPPLY
0
1000
2000
3000

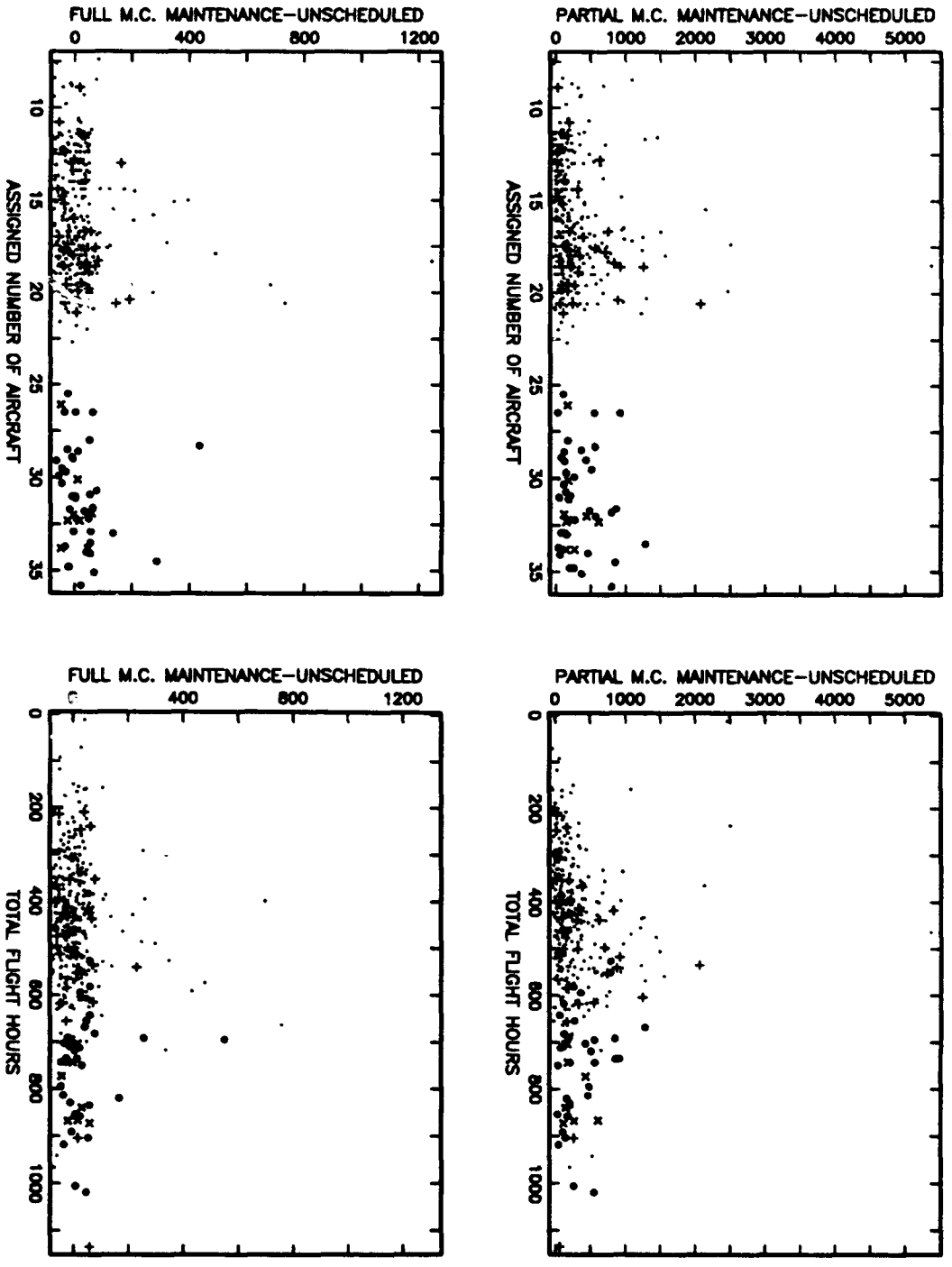

MISHAP SQUADRONS
NON MISHAP SQUADRONS
DENSITY
0
0.02
0.04
0.06
0
10
20
30
40
50
MAINTENANCE MAN HOURS PER FLIGHT HOUR

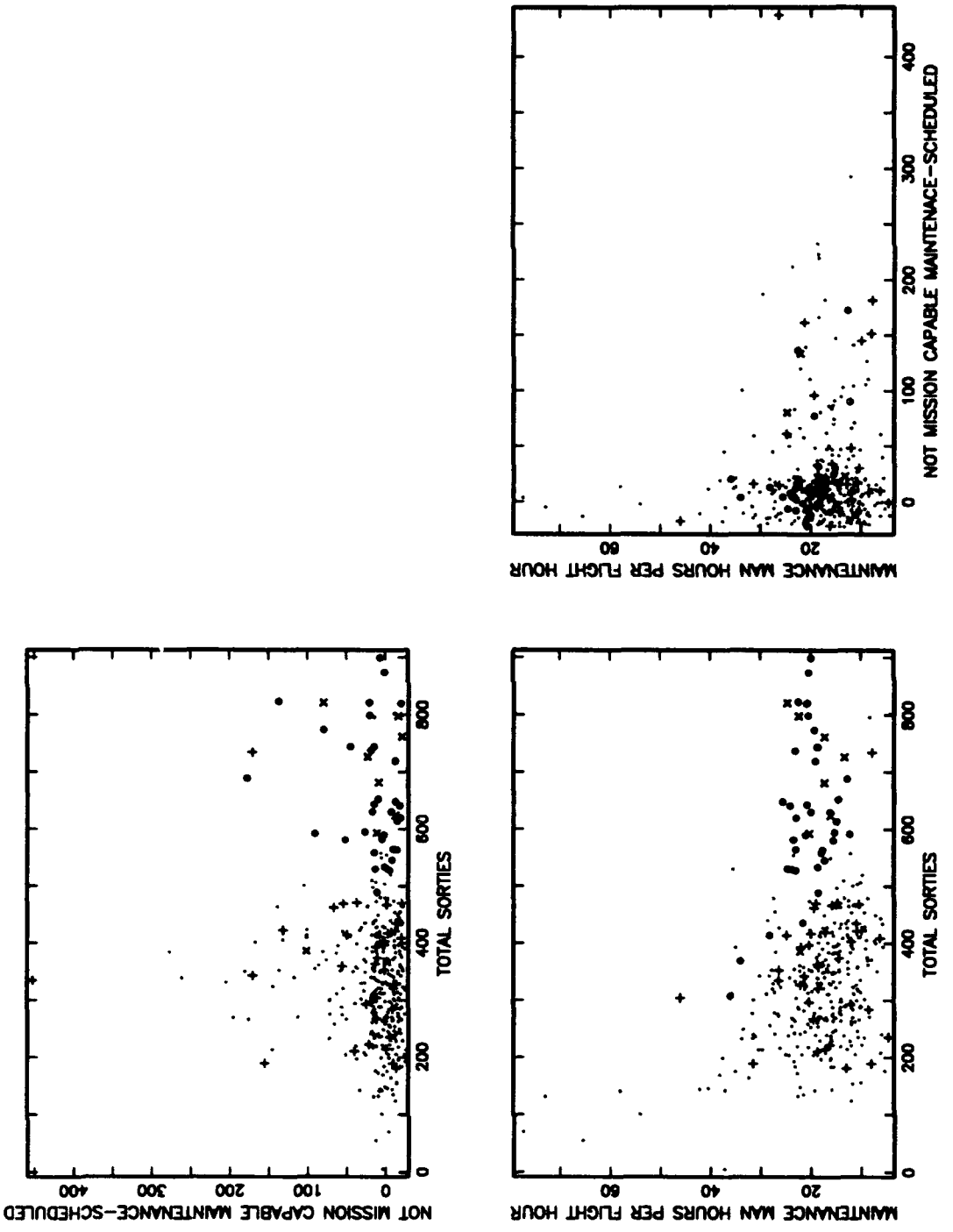
APPENDIX C. MAINTENANCE DATA CODED SCATTER PLOTS

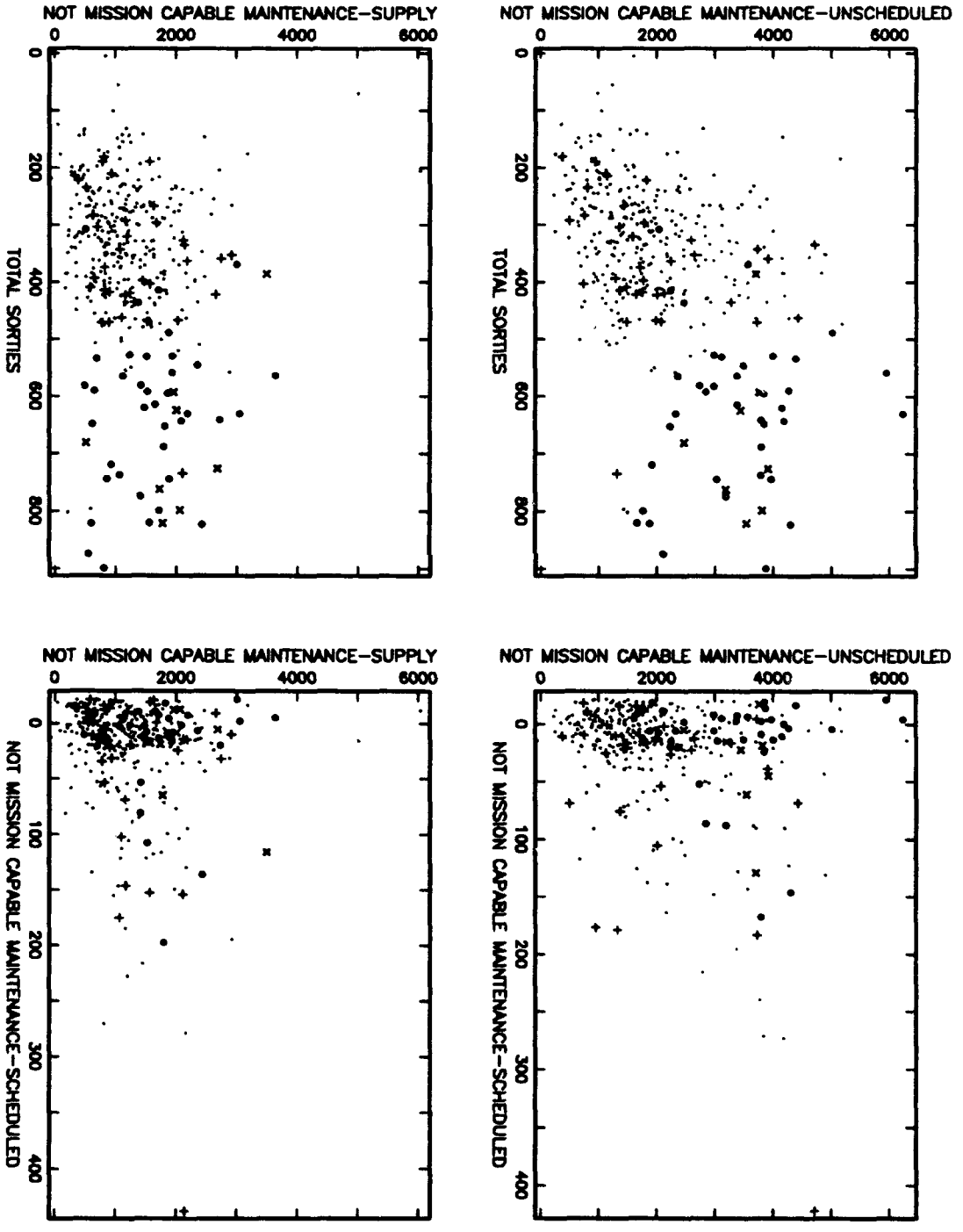


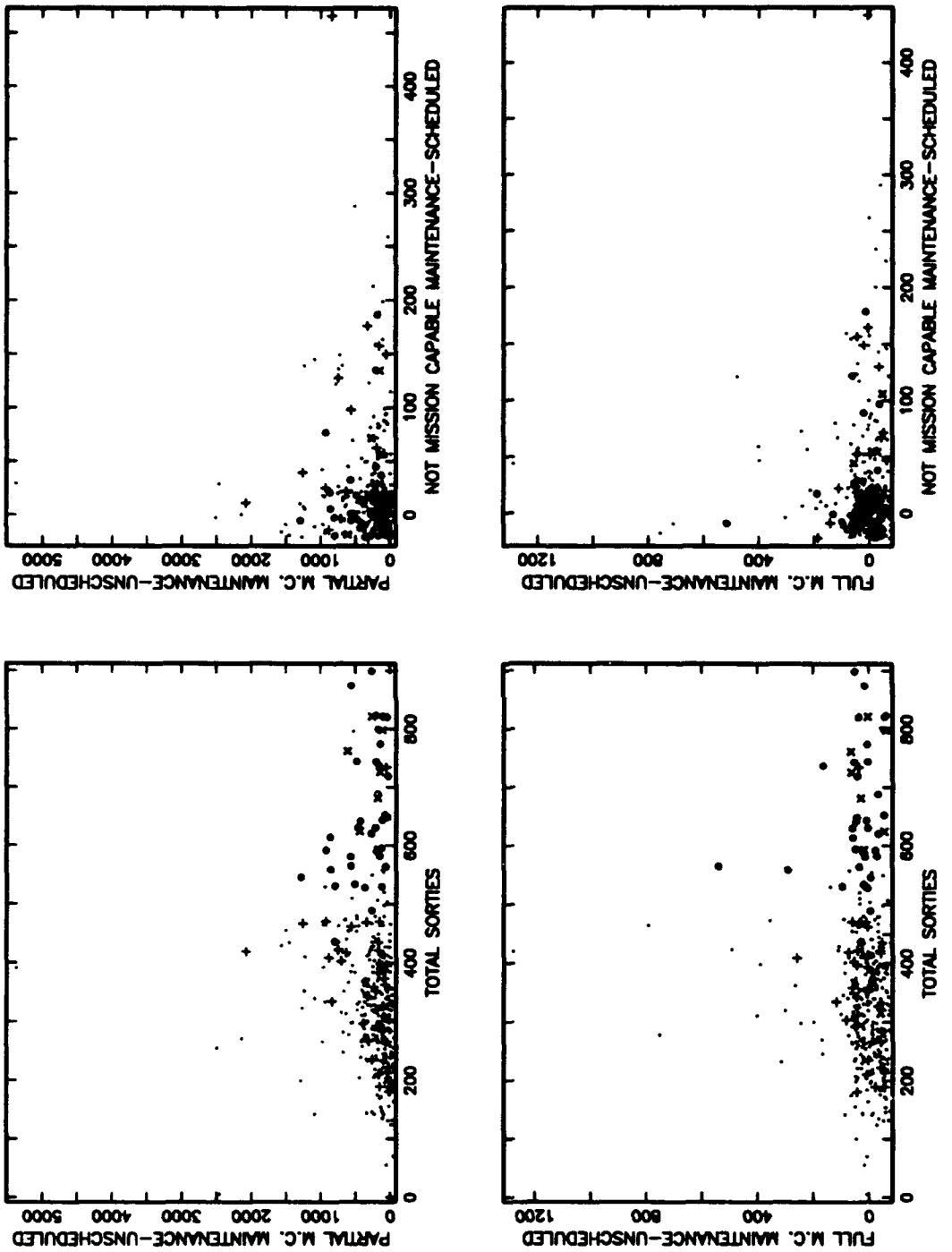

NOT MISSION CAPABLE MAINTENANCE–SCHEDULED
0
100
200
300
400
ASSIGNED NUMBER OF AIRCRAFT
10
15
20
25
30
35
NUMBER OF SORTIES
0
200
400
600
800
ASSIGNED NUMBER OF AIRCRAFT
10
15
20
25
30
35
NOT MISSION CAPABLE MAINTENANCE–SCHEDULED
0
100
200
300
400
TOTAL FLIGHT HOURS
0
200
400
600
800
1000
NUMBER OF SORTIES
0
200
400
600
800
TOTAL FLIGHT HOURS
0
200
400
600
800
1000

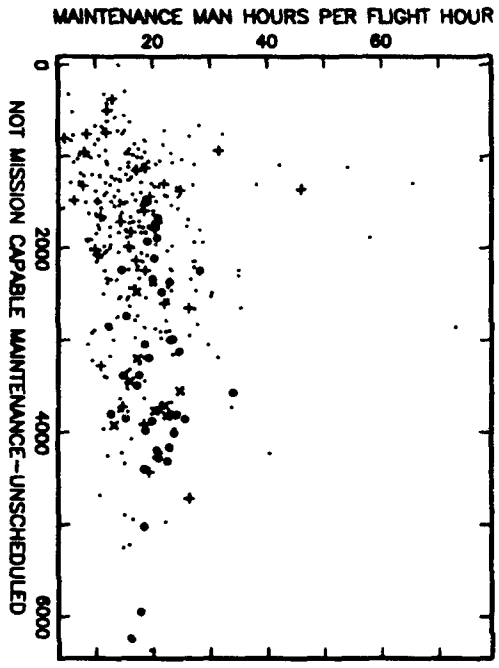

NOT MISSION CAPABLE MAINTENANCE-UNSCHEDULED
NOT MISSION CAPABLE MAINTENANCE-SUPPLY
TOTAL FLIGHT HOURS
ASSIGNED NUMBER OF AIRCRAFT
0
2000
4000
6000
200
400
600
800
1000
10
15
20
25
30
35

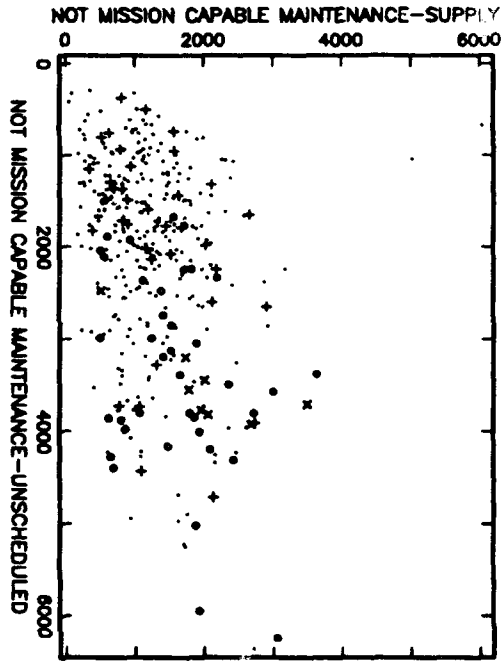

FULL M.C. MAINTENANCE–UNSCHEDULED
0
400
800
1200
ASSIGNED NUMBER OF AIRCRAFT
10
15
20
25
30
35
PARTIAL M.C. MAINTENANCE–UNSCHEDULED
0
1000
2000
3000
4000
5000
ASSIGNED NUMBER OF AIRCRAFT
10
15
20
25
30
35
FULL M.C. MAINTENANCE–UNSCHEDULED
0
400
800
1200
TOTAL FLIGHT HOURS
0
200
400
600
800
1000
PARTIAL M.C. MAINTENANCE–UNSCHEDULED
0
1000
2000
3000
4000
5000
TOTAL FLIGHT HOURS
0
200
400
600
800
1000

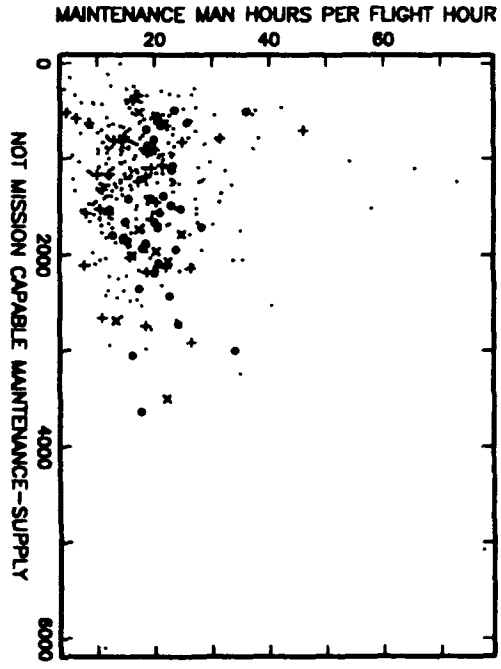

NOT MISSION CAPABLE MAINTENANCE-SCHEDULED
0
100
200
300
400
MAINTENANCE MAN HOURS PER FLIGHT HOUR
20
40
60
TOTAL SORTIES
0
200
400
600
800
NOT MISSION CAPABLE MAINTENANCE-SCHEDULED
0
100
200
300
400
TOTAL SORTIES
0
200
400
600
800
MAINTENANCE MAN HOURS PER FLIGHT HOUR
20
40
60

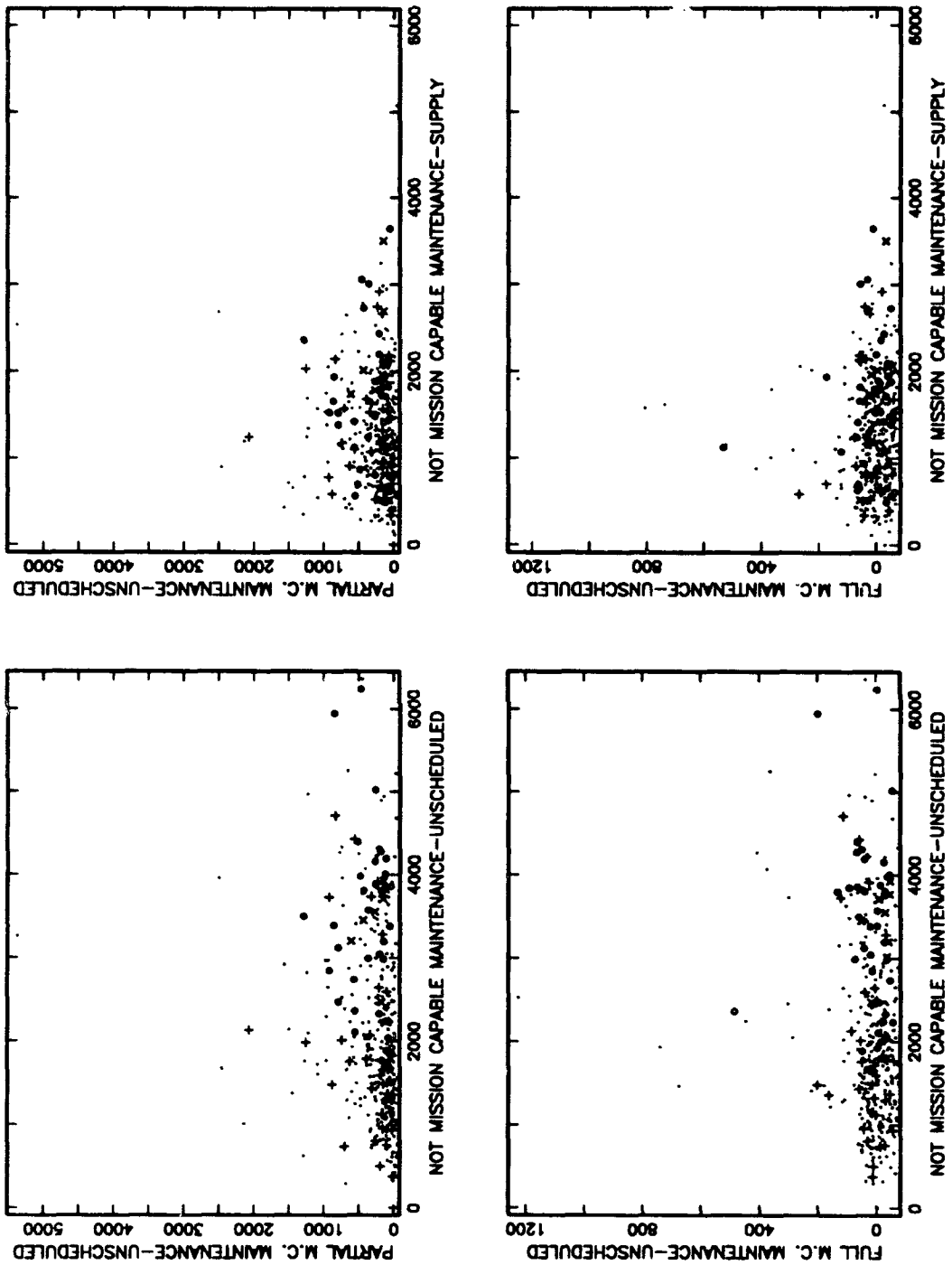

NOT MISSION CAPABLE MAINTENANCE–SUPPLY
0
2000
4000
6000
TOTAL SORTIES
0
200
400
600
800
NOT MISSION CAPABLE MAINTENANCE–UNSCHEDULED
0
2000
4000
6000
TOTAL SORTIES
0
200
400
600
800
NOT MISSION CAPABLE MAINTENANCE–SUPPLY
0
2000
4000
6000
NOT MISSION CAPABLE MAINTENANCE–SCHEDULED
0
100
200
300
400
NOT MISSION CAPABLE MAINTENANCE–UNSCHEDULED
0
2000
4000
6000
NOT MISSION CAPABLE MAINTENANCE–SCHEDULED
0
100
200
300
400

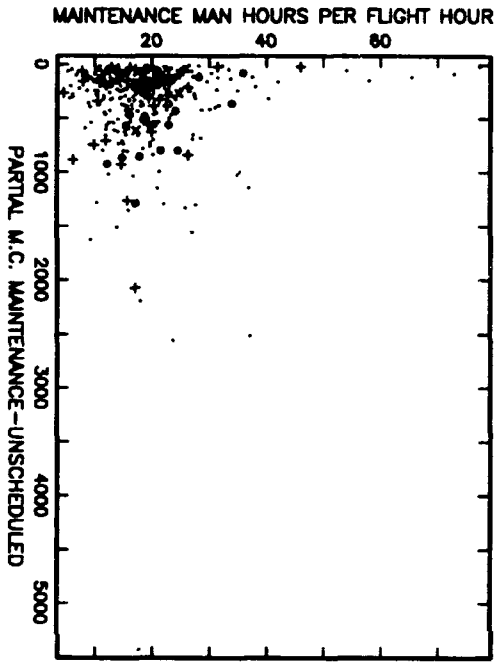

PARTIAL M.C. MAINTENANCE-UNSCHEDULED
0
1000
2000
3000
4000
5000
NOT MISSION CAPABLE MAINTENANCE-SCHEDULED
0
100
200
300
400
FULL M.C. MAINTENANCE-UNSCHEDULED
0
400
800
1200
NOT MISSION CAPABLE MAINTENANCE-SCHEDULED
0
100
200
300
400
PARTIAL M.C. MAINTENANCE-UNSCHEDULED
0
1000
2000
3000
4000
5000
TOTAL SORTIES
0
200
400
600
800
FULL M.C. MAINTENANCE-UNSCHEDULED
0
400
800
1200
TOTAL SORTIES
0
200
400
600
800

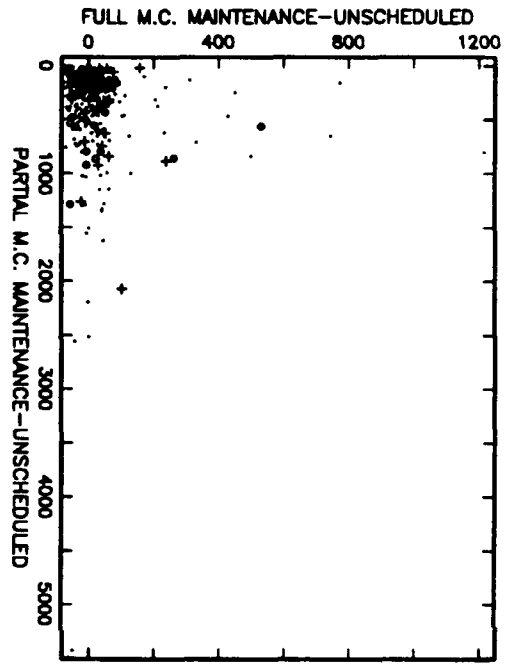

MAINTENANCE MAN HOURS PER FLIGHT HOUR
20
40
60
0
2000
4000
6000
NOT MISSION CAPABLE MAINTENANCE-UNSCHEDULED

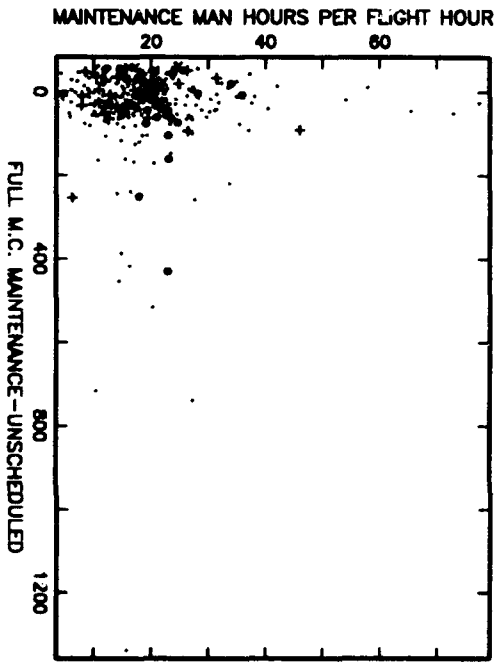

NOT MISSION CAPABLE MAINTENANCE-SUPPLY
0
2000
4000
6000
NOT MISSION CAPABLE MAINTENANCE-UNSCHEDULED


MAINTENANCE MAN HOURS PER FLIGHT HOUR
20
40
60
0
2000
4000
6000
NOT MISSION CAPABLE MAINTENANCE-SUPPLY

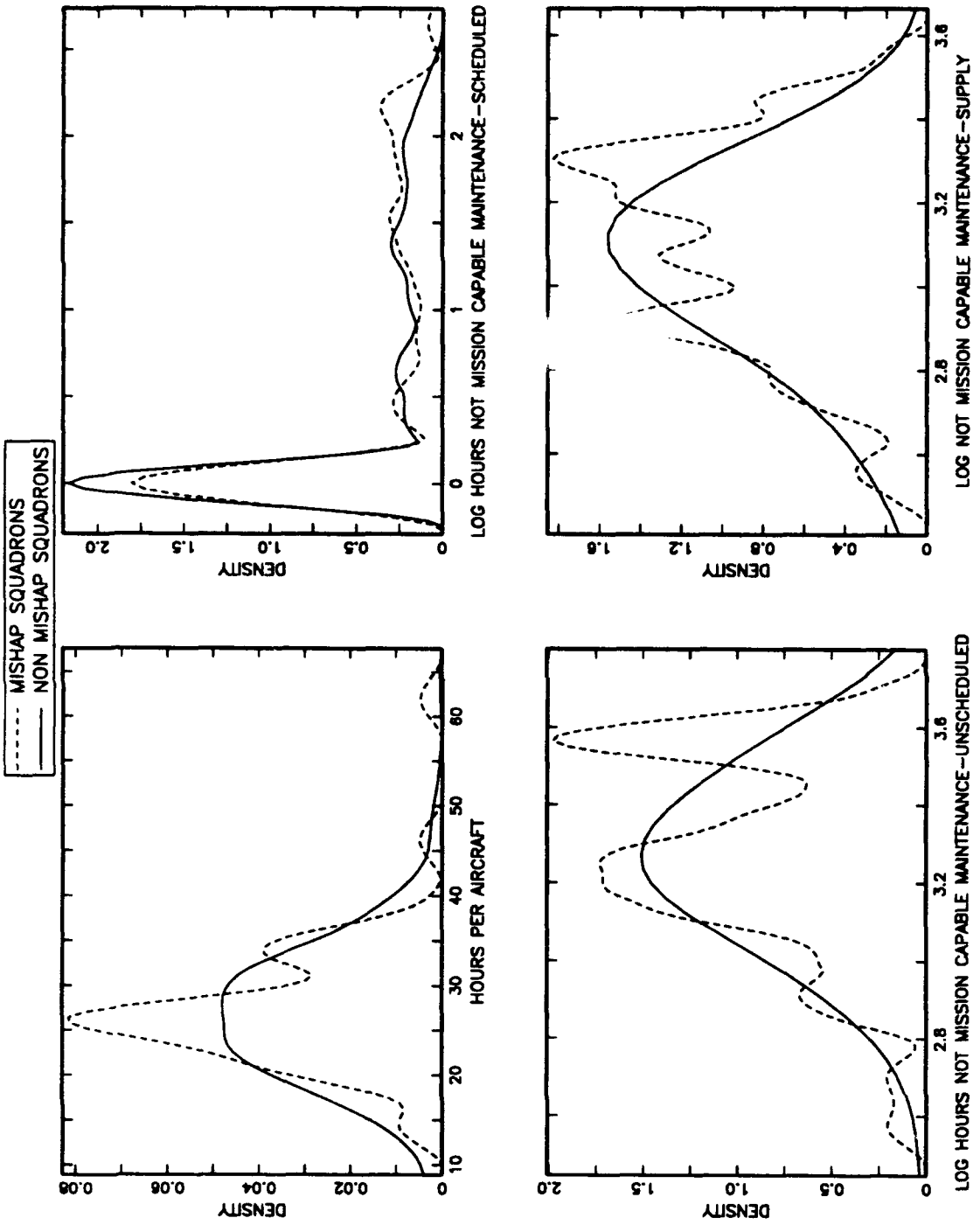

PARTIAL M.C. MAINTENANCE-UNSCHEDULED
0
1000
2000
3000
4000
5000
NOT MISSION CAPABLE MAINTENANCE-SUPPLY
0
2000
4000
6000
FULL M.C. MAINTENANCE-UNSCHEDULED
0
400
800
1200
NOT MISSION CAPABLE MAINTENANCE-SUPPLY
0
2000
4000
6000
PARTIAL M.C. MAINTENANCE-UNSCHEDULED
0
1000
2000
3000
4000
5000
NOT MISSION CAPABLE MAINTENANCE-UNSCHEDULED
0
2000
4000
6000
FULL M.C. MAINTENANCE-UNSCHEDULED
0
400
800
1200
NOT MISSION CAPABLE MAINTENANCE-UNSCHEDULED
0
2000
4000
6000

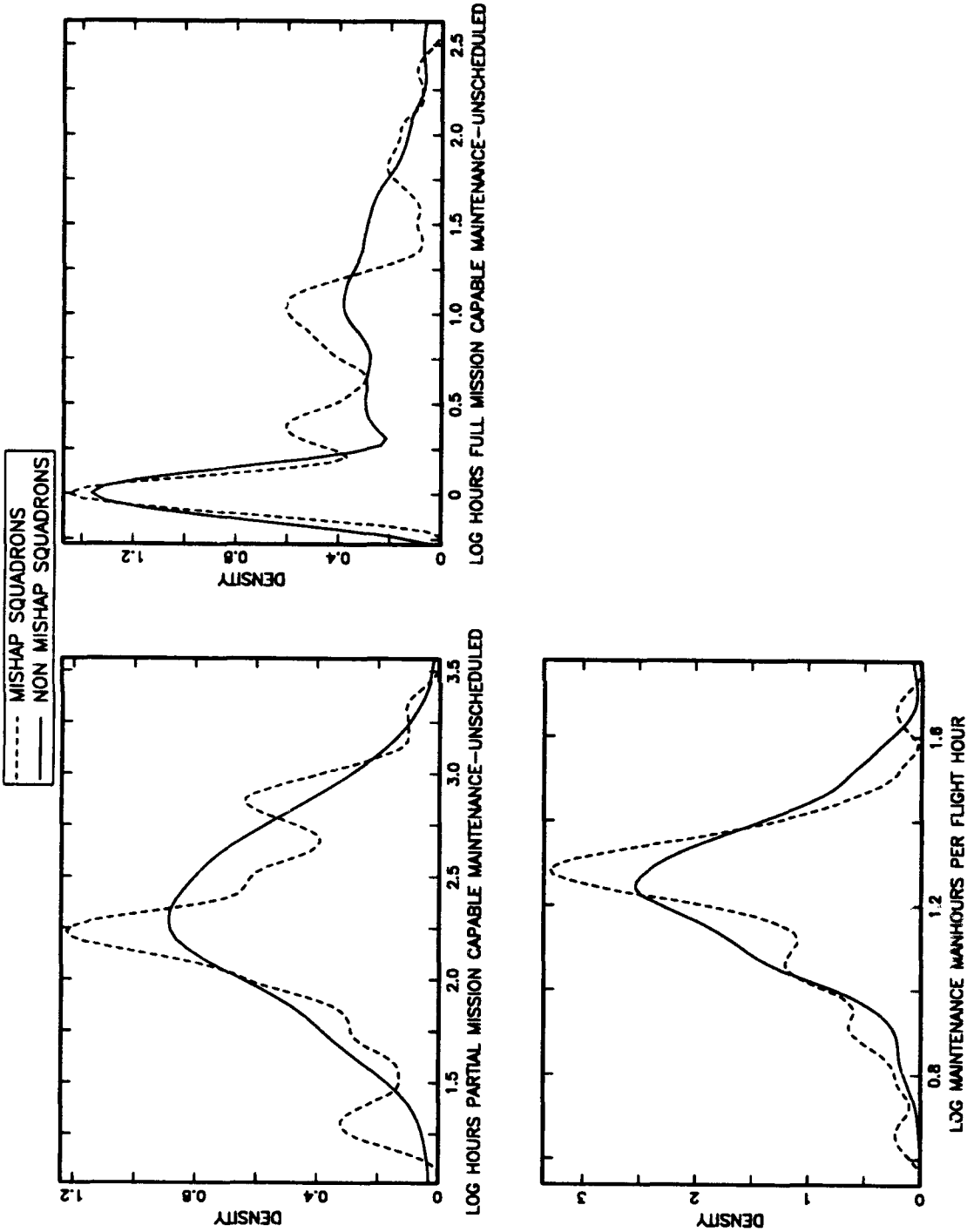

MAINTENANCE MAN HOURS PER FLIGHT HOUR
20
40
60
0
1000
2000
3000
4000
5000
PARTIAL M.C. MAINTENANCE-UNSCHEDULED


FULL M.C. MAINTENANCE-UNSCHEDULED
0
400
800
1200
0
1000
2000
3000
4000
5000
PARTIAL M.C. MAINTENANCE-UNSCHEDULED

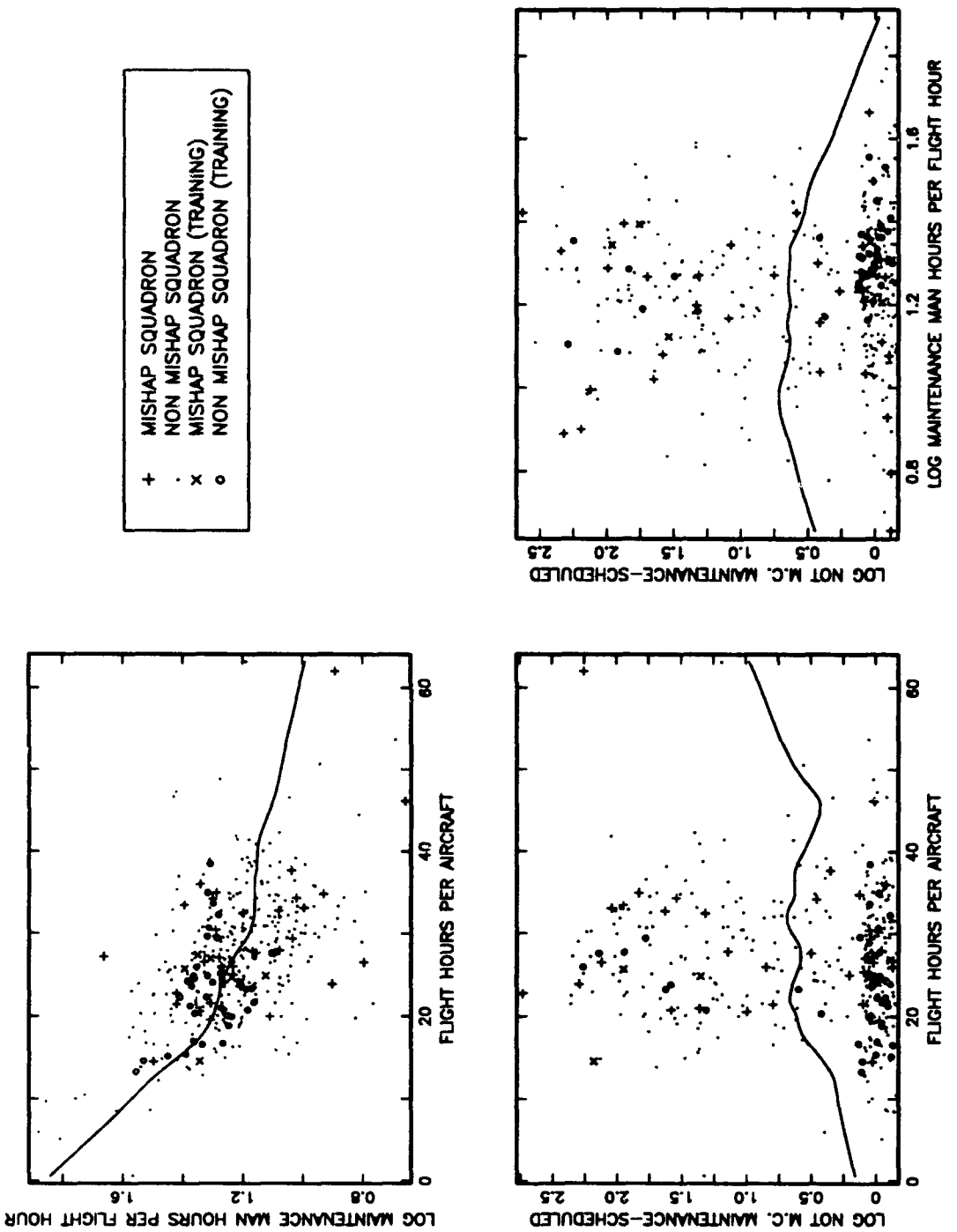

MAINTENANCE MAN HOURS PER FLIGHT HOUR
20
40
60
0
400
800
1200
FULL M.C. MAINTENANCE-UNSCHEDULED

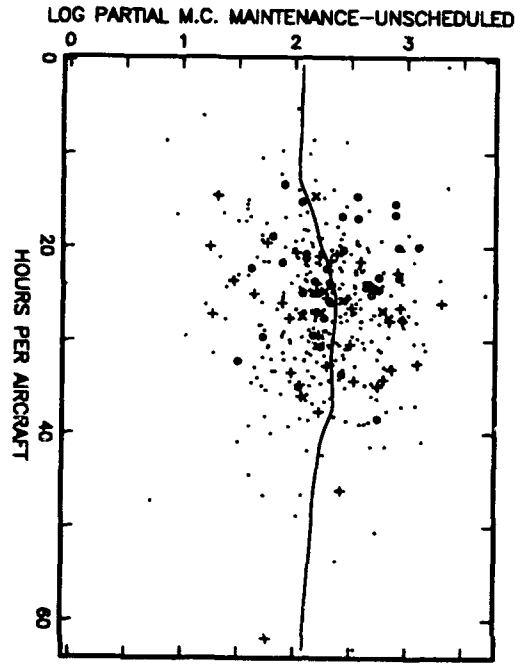
APPENDIX D. TRANSFORMED MAINTENANCE DATA DENSITY TRACES

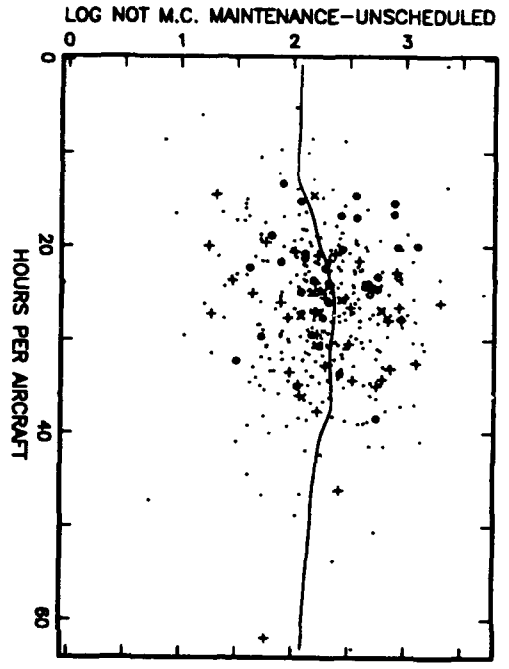


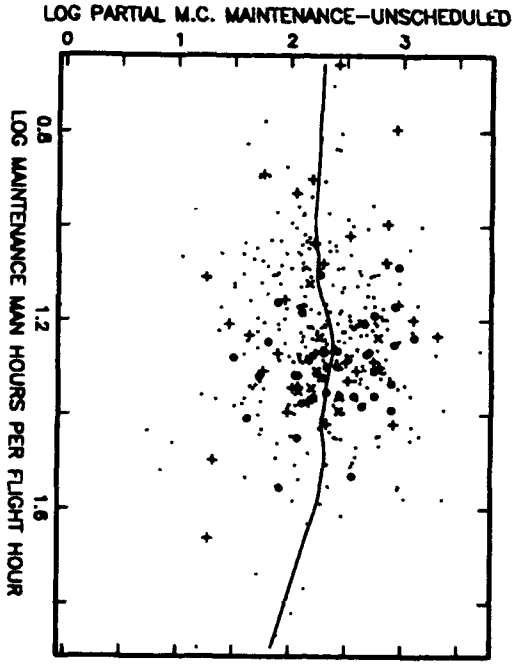

MISHAP SQUADRONS
NON MISHAP SQUADRONS
DENSITY
LOG HOURS FULL MISSION CAPABLE MAINTENANCE-UNSCHEDULED
LOG HOURS PARTIAL MISSION CAPABLE MAINTENANCE-UNSCHEDULED
LOG MAINTENANCE MANHOURS PER FLIGHT HOUR

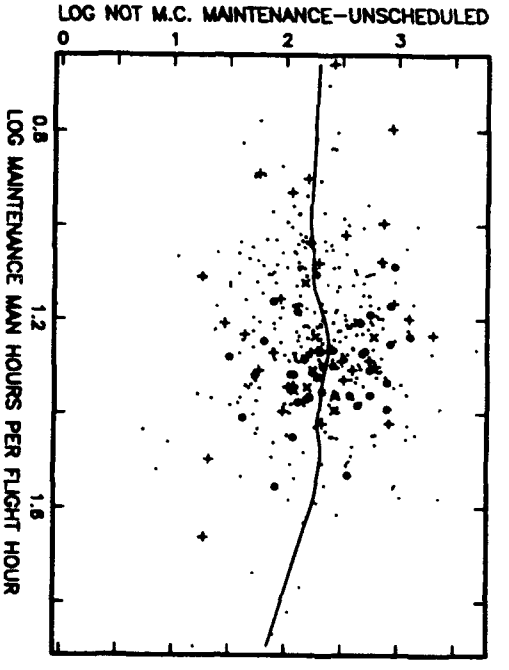
APPENDIX E. TRANSFORMED MAINTENANCE DATA CODED SCATTER PLOTS

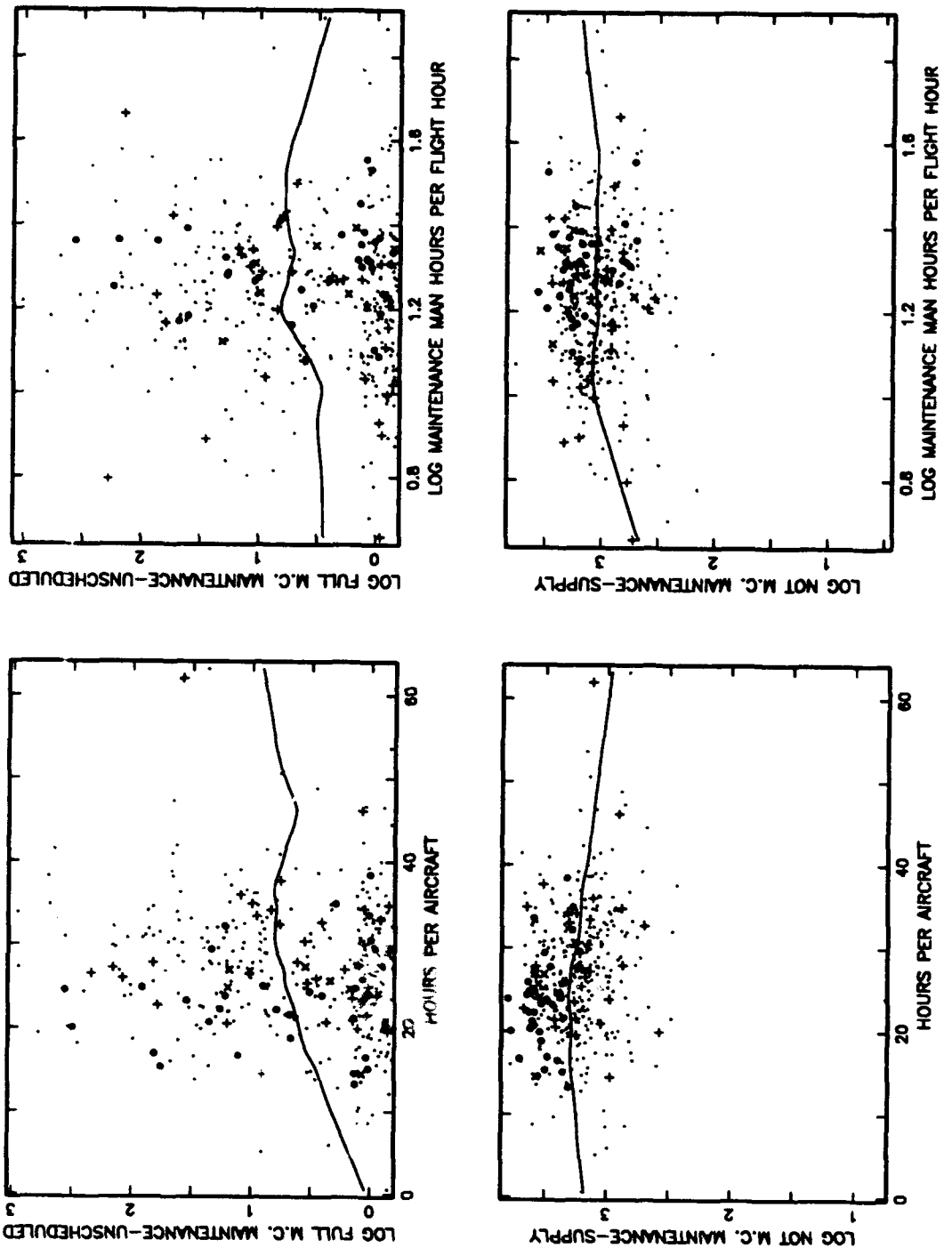


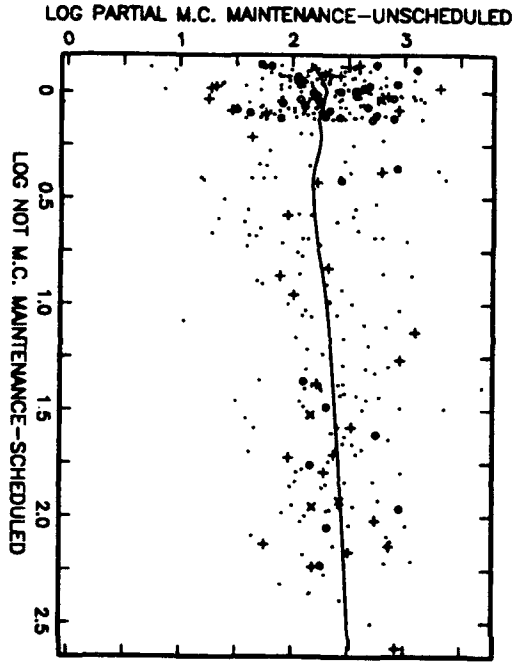

LOG PARTIAL M.C. MAINTENANCE–UNSCHEDULED
0
1
2
3
0
20
40
60
HOURS PER AIRCRAFT

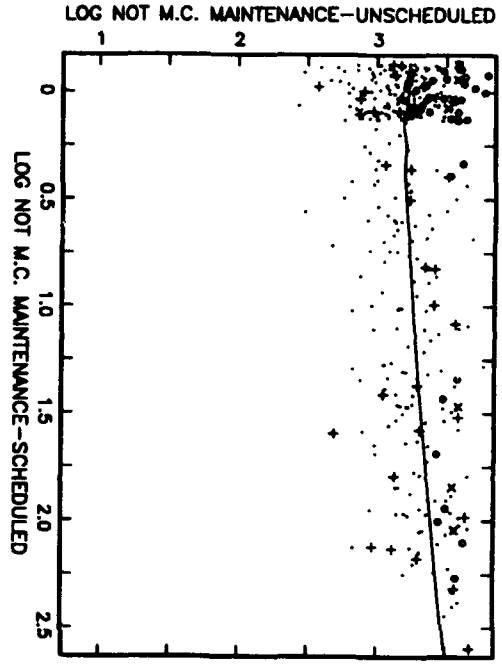

LOG NOT M.C. MAINTENANCE–UNSCHEDULED
0
1
2
3
0
20
40
60
HOURS PER AIRCRAFT

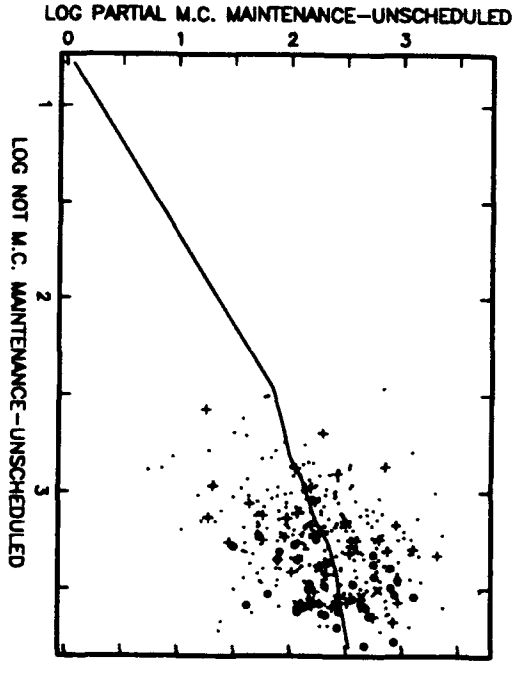

LOG PARTIAL M.C. MAINTENANCE–UNSCHEDULED
0
1
2
3
0.8
1.2
1.6
LOG MAINTENANCE MAN HOURS PER FLIGHT HOUR

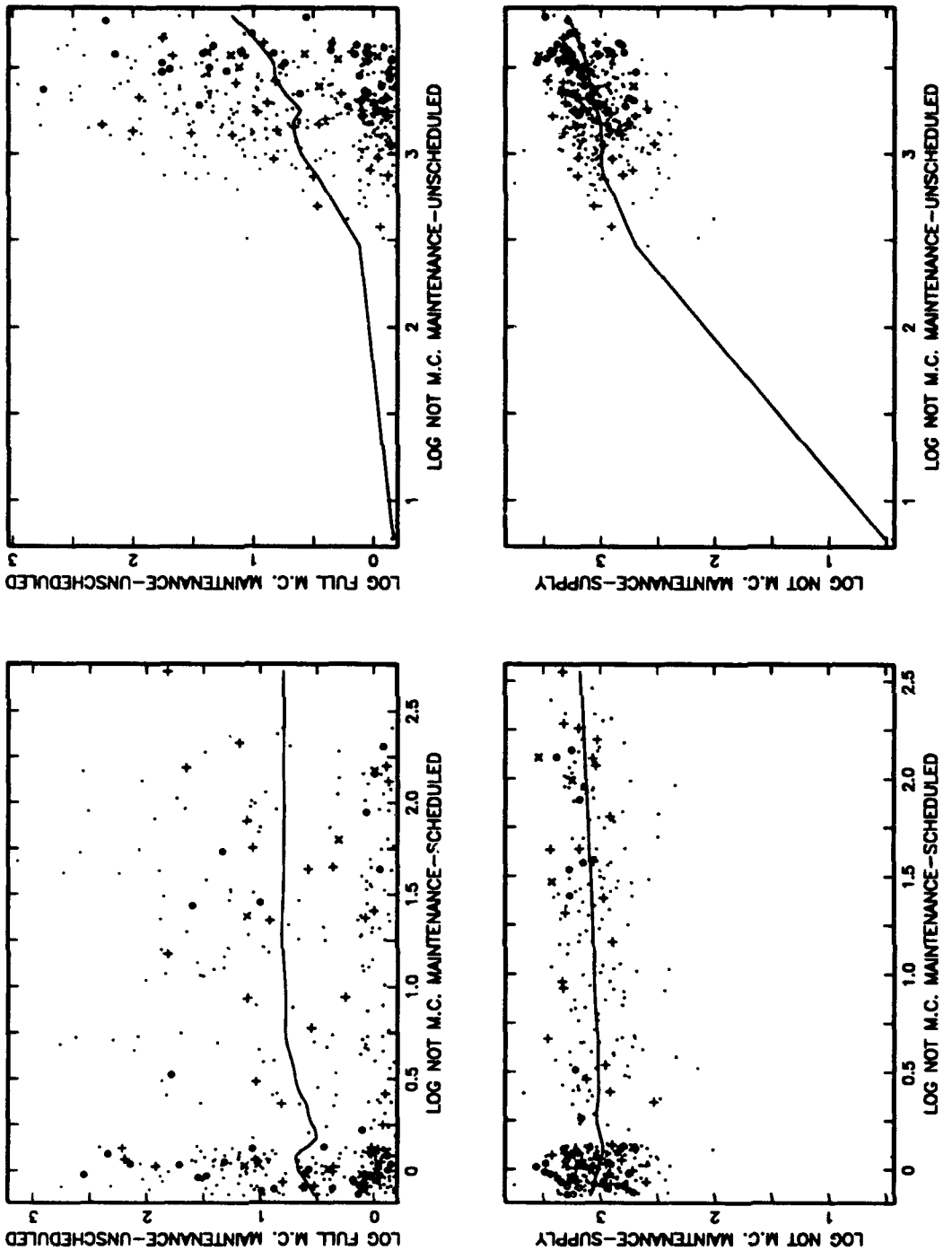

LOG NOT M.C. MAINTENANCE–UNSCHEDULED
0
1
2
3
0.8
1.2
1.6
LOG MAINTENANCE MAN HOURS PER FLIGHT HOUR

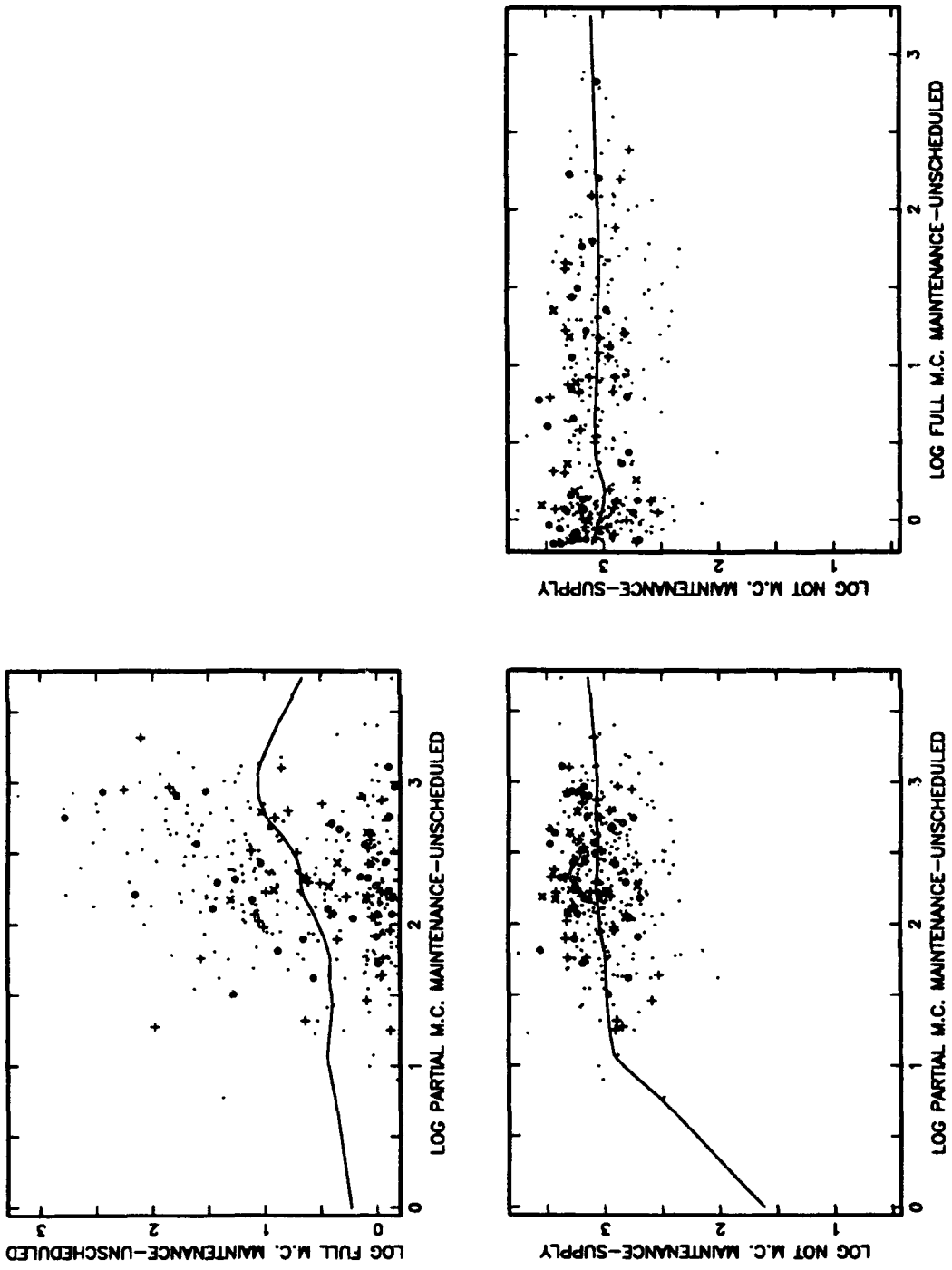

LOG FULL M.C. MAINTENANCE-UNSCHEDULED
LOG MAINTENANCE MAN HOURS PER FLIGHT HOUR
LOG NOT M.C. MAINTENANCE-SUPPLY
LOG MAINTENANCE MAN HOURS PER FLIGHT HOUR
LOG FULL M.C. MAINTENANCE-UNSCHEDULED
HOURS PER AIRCRAFT
LOG NOT M.C. MAINTENANCE-SUPPLY
HOURS PER AIRCRAFT


LOG PARTIAL M.C. MAINTENANCE–UNSCHEDULED
0
1
2
3
LOG NOT M.C. MAINTENANCE–SCHEDULED
0
0.5
1.0
1.5
2.0
2.5


LOG NOT M.C. MAINTENANCE–UNSCHEDULED
1
2
3
LOG NOT M.C. MAINTENANCE–SCHEDULED
0
0.5
1.0
1.5
2.0
2.5


LOG PARTIAL M.C. MAINTENANCE–UNSCHEDULED
0
1
2
3
LOG NOT M.C. MAINTENANCE–UNSCHEDULED
0
1
2
3


LOG FULL M.C. MAINTENANCE-UNSCHEDULED
LOG NOT M.C. MAINTENANCE-UNSCHEDULED
LOG NOT M.C. MAINTENANCE-SUPPLY
LOG NOT M.C. MAINTENANCE-SCHEDULED


LOG NOT M.C. MAINTENANCE-SUPPLY
LOG FULL M.C. MAINTENANCE-UNSCHEDULED
LOG NOT M.C. MAINTENANCE-SUPPLY
LOG PARTIAL M.C. MAINTENANCE-UNSCHEDULED
LOG FULL M.C. MAINTENANCE-UNSCHEDULED
LOG PARTIAL M.C. MAINTENANCE-UNSCHEDULED

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